Why would  $\varphi_B$  be any better than  $\varphi$ ?

#### Illustration on the regression case:

Suppose (X,Y) drawn from distribution  $P_{X,Y}$ .  $\varphi$  predictor trained on  $\mathcal T$  or any bootstrap sample of  $\mathcal T$   $\hat{P}_{\mathcal T} \text{ empirical distribution of } \mathcal T$   $P_{\mathcal T} \text{ true distribution of } \mathcal T$  To simplify notation:  $\mathbb E_{P_{X,Y}} = \mathbb E_{X,Y}, \ \mathbb E_{P_{\mathcal T}} = \mathbb E_{\mathcal T} \text{ and } \mathbb E_{\hat{P}_{\mathcal T}} = \mathbb E_{\hat{\mathcal T}}.$   $\varphi_B(\cdot) = \mathbb E_{\hat{\mathcal T}} \left( \varphi(\cdot) \right) \text{ Bagging predictor}$   $\varphi_A(\cdot) = \mathbb E_{\mathcal T} \left( \varphi(\cdot) \right) \text{ aggregated predictor}$ 

Average prediction error of 
$$\varphi_A$$
:  $e_A = \mathbb{E}_{X,Y}\left(\left[Y - \varphi_A\left(X\right)\right]^2\right)$ .

Average prediction error of  $\varphi$ :  $e = \mathbb{E}_{\mathcal{T}}\left(\mathbb{E}_{X,Y}\left([Y - \varphi(X)]^2\right)\right)$ . Average prediction error of  $\varphi_A$ :  $e_A = \mathbb{E}_{X,Y}\left([Y - \varphi_A(X)]^2\right)$ .

Average prediction error of 
$$\varphi_{A}$$
.  $e_{A} = \mathbb{E}_{X,Y}\left(\left[T - \varphi_{A}\left(X\right)\right]\right)$ . 
$$e = \mathbb{E}_{X,Y}\left(Y^{2}\right) - 2\mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(Y\varphi\left(X\right)\right)\right) + \mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(\left[\varphi(X)\right]^{2}\right)\right)$$

Average prediction error of  $\varphi$ :  $e = \mathbb{E}_{\mathcal{T}}\left(\mathbb{E}_{X,Y}\left([Y-\varphi(X)]^2\right)\right)$ . Average prediction error of  $\varphi_A$ :  $e_A = \mathbb{E}_{X,Y}\left([Y-\varphi_A(X)]^2\right)$ .  $e = \mathbb{E}_{X,Y}\left(Y^2\right) - 2\mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(Y\varphi(X)\right)\right) + \mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left([\varphi(X)]^2\right)\right)$ 

Average prediction error of 
$$\varphi_A$$
:  $e_A = \mathbb{E}_{X,Y} \left( \left[ Y - \varphi_A \left( X \right) \right]^2 \right)$ .  $e = \mathbb{E}_{X,Y} \left( Y^2 \right) - 2\mathbb{E}_{X,Y} \left( Y \varphi_A(X) \right) + \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( \left[ \varphi(X) \right]^2 \right) \right)$ 

Average prediction error of  $\varphi$ :  $e = \mathbb{E}_{\mathcal{T}}\left(\mathbb{E}_{X,Y}\left(\left[Y - \varphi\left(X\right)\right]^{2}\right)\right)$ .

Average prediction error of  $\varphi_A$ :  $e_A = \mathbb{E}_{X,Y}\left(\left[Y - \varphi_A\left(X\right)\right]^2\right)$ .

Average prediction error of 
$$\varphi_A$$
:  $e_A = \mathbb{E}_{X,Y} \left( [Y - \varphi_A(X)] \right)$ .  $e = \mathbb{E}_{X,Y} \left( Y^2 \right) - 2\mathbb{E}_{X,Y} \left( Y\varphi_A(X) \right) + \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) \right)$  But  $\mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) \right) \geq \mathbb{E}_{X,Y} \left( [\mathbb{E}_{\mathcal{T}} \left( \varphi(X) \right)]^2 \right)$ 

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:  $e_A = \mathbb{E}_{X,Y}\left(\left[Y - \varphi_A\left(X\right)\right]^2\right)$ .

Average prediction error of 
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.  $e_A = \mathbb{E}_{X,Y} \left( [T - \varphi_A(X)] \right)$ .  $e = \mathbb{E}_{X,Y} \left( Y^2 - 2\mathbb{E}_{X,Y} \left( Y\varphi_A(X) \right) + \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) \right) \right)$  But  $\mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) \right) \geq \mathbb{E}_{X,Y} \left( [\mathbb{E}_{\mathcal{T}} \left( \varphi(X) \right)]^2 \right)$ 

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Average prediction error of  $\varphi$ :  $e = \mathbb{E}_{\mathcal{T}}\left(\mathbb{E}_{X,Y}\left(\left[Y - \varphi\left(X\right)\right]^{2}\right)\right)$ .

Average prediction error of 
$$\varphi_A$$
:  $e_A = \mathbb{E}_{X,Y} \left( [Y - \varphi_A(X)]^2 \right)$ .
$$e = \mathbb{E}_{X,Y} \left( Y^2 - 2\mathbb{E}_{X,Y} \left( Y(\varphi_A(X)) + \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) \right) \right)$$

$$e = \mathbb{E}_{X,Y}\left(Y^2\right) - 2\mathbb{E}_{X,Y}\left(Y\varphi_A(X)\right) + \mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(\left[\varphi(X)\right]^2\right)\right)$$
 But  $\mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(\left[\varphi(X)\right]^2\right)\right) \ge \mathbb{E}_{X,Y}\left(\left[\varphi_A(X)\right]^2\right)$ 

So  $e > e_A$ .

Average prediction error of 
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Average prediction error of 
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:  $e_A = \mathbb{E}_{X,Y} \left( [Y - \varphi_A(X)] \right)$ .  $e = \mathbb{E}_{X,Y} \left( Y^2 \right) - 2\mathbb{E}_{X,Y} \left( Y\varphi_A(X) \right) + \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) \right)$ 

But 
$$\mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(\left[\varphi(X)\right]^{2}\right)\right) \geq \mathbb{E}_{X,Y}\left(\left[\varphi_{A}(X)\right]^{2}\right)$$
  
So  $e \geq e_{A}$ .  
Moreover:  
 $e - e_{A} = \mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(\left[\varphi(X)\right]^{2}\right) - \left[\mathbb{E}_{\mathcal{T}}\left(\varphi(X)\right]^{2}\right)$ 

$$\begin{aligned} & \text{Moreover:} \\ & e - e_A = \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( \left[ \varphi(X) \right]^2 \right) - \left[ \mathbb{E}_{\mathcal{T}} \left( \varphi(X) \right) \right]^2 \right) \\ & e - e_A = \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( \left[ \varphi(X) \right]^2 \right) - \left[ \varphi_A(X) \right]^2 \right) \end{aligned}$$

Average prediction error of  $\varphi$ :  $e = \mathbb{E}_{\mathcal{T}}\left(\mathbb{E}_{X,Y}\left(\left[Y - \varphi\left(X\right)\right]^{2}\right)\right)$ .

Average prediction error of 
$$\varphi_A$$
:  $e_A = \mathbb{E}_{X,Y}\left(\left[Y - \varphi_A\left(X\right)\right]^2\right)$ .

$$e = \mathbb{E}_{X,Y} (Y^2) - 2\mathbb{E}_{X,Y} (Y\varphi_A(X)) + \mathbb{E}_{X,Y} (\mathbb{E}_{\mathcal{T}} ([\varphi(X)]^2))$$

But 
$$\mathbb{E}_{X,Y}\left(\mathbb{E}_{\mathcal{T}}\left(\left[\varphi(X)\right]^{2}\right)\right) \geq \mathbb{E}_{X,Y}\left(\left[\varphi_{A}(X)\right]^{2}\right)$$
 So  $e \geq e_{A}$ .

Moreover:

wherever,
$$e - e_A = \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) - [\mathbb{E}_{\mathcal{T}} (\varphi(X))]^2 \right)$$

$$e - e_A = \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) - [\varphi_A(X)]^2 \right)$$

$$-e_A = \mathbb{E}_{X,Y} \left( \mathbb{E}_{\mathcal{T}} \left( [\varphi(X)]^2 \right) - [\varphi_A(X)]^2 \right)$$

Interpretation: if  $\varphi_{\mathcal{T}}$  differs a lot from  $\varphi_{\mathcal{T}'}$ , then  $e - e_A$  is large.  $\Rightarrow$  The highest the variance of  $\varphi$  across training sets  $\mathcal{T}$ , the more improvement  $\varphi_A$  produces.

Ok, so  $\varphi_A$  always improves on  $\varphi$ , especially when  $\varphi$  is highly variable w.r.t. changes in  $\mathcal{T}$ .

Ok, so  $\varphi_A$  always improves on  $\varphi$ , especially when  $\varphi$  is highly variable w.r.t. changes in  $\mathcal T$ .

 $\begin{array}{c} \text{But } \varphi_A \text{ is not } \varphi_B. \text{ Recall:} \\ \varphi_A(\cdot) = \mathbb{E}_{\mathcal{T}}\left(\varphi(\cdot)\right) \text{ aggregated predictor (over all $N$-size training sets)} \\ \varphi_B(\cdot) = \mathbb{E}_{\hat{\mathcal{T}}}\left(\varphi(\cdot)\right) \text{ Bagging predictor (over bootstrap samples)} \\ \varphi_B \text{ approximates } \varphi_A \text{ and thus } e_B \geq e_A \end{array}$ 

Ok, so  $\varphi_A$  always improves on  $\varphi$ , especially when  $\varphi$  is highly variable w.r.t. changes in  $\mathcal T$ .

But  $\varphi_A$  is not  $\varphi_B$ . Recall:

$$\begin{split} \varphi_A(\cdot) &= \mathbb{E}_{\mathcal{T}}\left(\varphi(\cdot)\right) \text{ aggregated predictor (over all $N$-size training sets)} \\ \varphi_B(\cdot) &= \mathbb{E}_{\hat{\mathcal{T}}}\left(\varphi(\cdot)\right) \text{ Bagging predictor (over bootstrap samples)} \\ \varphi_B \text{ approximates } \varphi_A \text{ and thus } e_B \geq e_A \end{split}$$

- lacktriangle If arphi highly variable w.r.t.  $\mathcal{T}$ ,  $arphi_B$  improves on arphi through aggregation.
- ▶ But if  $\varphi$  is rather stable w.r.t.  $\mathcal{T}$ ,  $e_A \approx e$  and since  $\varphi_B$  approximates  $\varphi_A$ ,  $e_B$  might be greater than e.

So it does not always work?

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Actually, no, it does not always work.

Bagging should be used to transform highly variable predictors  $\varphi$  into a more accurate averaged commitee  $\varphi_B$ .

Examples of  $\varphi$  that Bagging improve:

- $\rightarrow$  Trees, Neural Networks.
- Examples of  $\varphi$  that Bagging does not improve much (or degrades):
- → Support Vector Machines, Gaussian Processes.

And in the classification case?

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Majority vote: 
$$\varphi_B(x) = \arg\max_j \sum_{b=1}^B I(\varphi^b(x) = j)$$

More drastic conclusions:

- ullet arphi unstable w.r.t.  ${\mathcal T}$  and reasonable performance  $\Rightarrow arphi_B$  near optimal.
- $\varphi$  stable w.r.t.  $\mathcal{T}\Rightarrow \varphi_B$  worse than  $\varphi$ .
- $\varphi$  poor performance  $\Rightarrow \varphi_B$  worse than  $\varphi$ .