



Certifying Out-of-Domain Generalization for Blackbox Functions

Maurice Weber¹ Linyi Li² Boxin Wang² Zhikuan Zhao¹ Bo Li¹ Ce Zhang¹

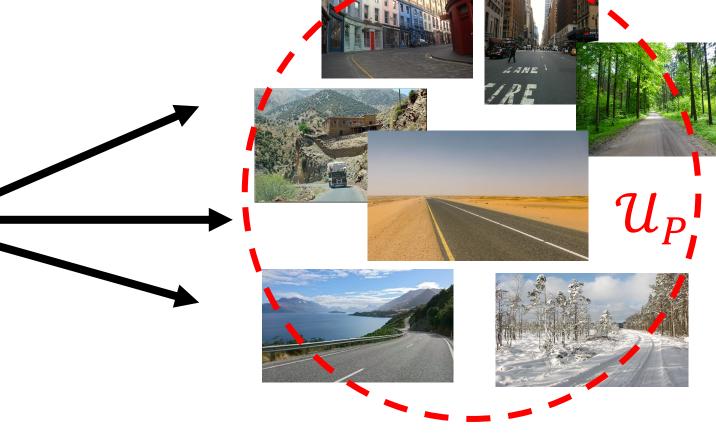
¹ETH Zürich

²University of Illinois Urbana-Champaign

Motivation



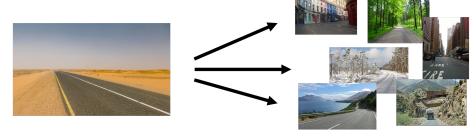
Train Distribution P



Test Distributions $Q \in \mathcal{U}_P$

<u>Certificate:</u> $\forall Q$: dist $(P,Q) \leq \rho \implies E_{Z\sim Q}[\ell(Z)] \leq C_{\ell}(\rho,P)$

Main Contributions



Train Distribution P

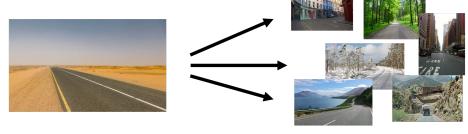
Test Distributions $Q \in \mathcal{U}_P$

Provide a rigorous upper bound $C_{\ell}(\rho, P)$ with

$$\sup_{Q \in \mathcal{U}_P} E_{Z \sim Q}[\ell(Z)] \le C_{\ell}(\rho, P)$$

- \succ under minimal assumptions on the model ℓ (black-box)
- \succ that can be estimated from a finite, in-domain sample $Z_1, \dots, Z_n \sim P$
- > which scales to *large datasets* and state-of-the-art *neural networks*

Certifying Out-of-Domain Generalization



Train Distribution P

Test Distributions $Q \in \mathcal{U}_P$

$$\sup_{Q \in \mathcal{U}_P} E_{Z \sim Q}[\ell(Z)] \le C_{\ell}(\rho, P)$$

Uncertainty Set:

 $\mathcal{U}_P = \{Q \mid H(P, \mathbf{Q}) \leq \rho\},$

(H = Hellinger distance)

Model / Loss function:

 $\forall z \in \mathcal{Z} : 0 \leq \ell(z) \leq M$

(Boundedness, Positivity)

Technique

- 1. Express Expectation values as inner products
- 2. Use Non-negativity of Gram matrices to get a robustness condition

Main Result

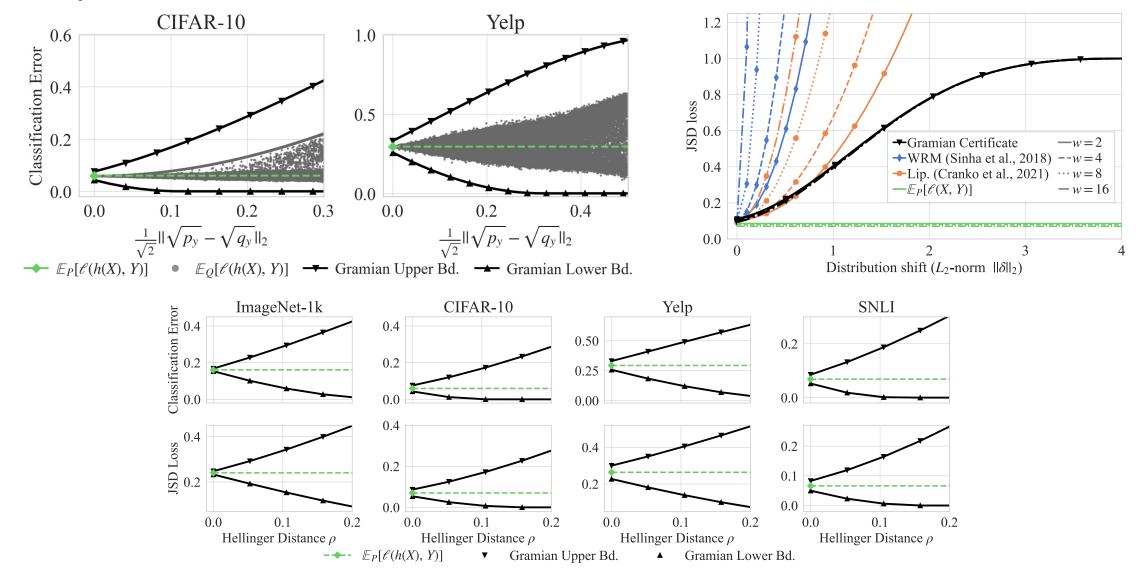
Let ℓ : $\mathcal{Z} \to [0, M]$ be a loss function, P a probability measure on \mathcal{Z} . For $\rho > 0$, we have

$$\sup_{\mathbf{Q}: H(P,\mathbf{Q}) \le \rho} E_{\mathbf{Q}}[\ell] \le E_{\mathbf{P}}[\ell] + 2C_{\rho}\sqrt{V_{\mathbf{P}}[\ell]} + \phi_{M,\rho}(E_{\mathbf{P}}[\ell], V_{\mathbf{P}}[\ell])$$

where ρ is required to satisfy $\rho^2 \leq 1 - \left[1 + \frac{(M - E_P[\ell])^2}{V_P[\ell]}\right]^{-1/2}$.

- \longrightarrow Bound only requires **blackbox** access to the model ℓ .
- Can be estimated from *finite samples* using concentration inequalities.
- \longrightarrow Monotonically increasing in $E_P[\ell]$ and $V_P[\ell]$.

Experiments



Conclusion and Outlook

- We have presented a technique to *certify out-of-domain generalization*
 - > for uncertainty sets defined via the *Hellinger* distance
 - > which only requires **blackbox** access to the model and loss function
 - > and hence scales to *large-scale* models and datasets

Future work

- > explore more *specific distribution shifts* to get tighter certificates
- > different *applications*, beyond classification tasks