Introduction

- Domain generalization: learn a classifier from a set of training domains that generalizes to test domains.
- Prior work on domain-invariant representation learning minimizes the average risk across all domains $\{f_i\}$. The invariant classifier will not coincide with the pointwise-optimal classifier per domain. $\{f_1, f_2, \ldots, f_n\}$
- can we create a domain-specific adaptive classifier for domain generalization?

Our Approach

Learn an adaptive classifier $F$ on both the input $x$ and the domain $D$ that $x$ belongs to, by computing a kernel mean embedding $\varphi$ of the domain $D$ via samples. This involves 3 steps:

1. **Learning a good embedding**: To learn the embedding $\varphi$, we use a low-shot learning method called prototypical networks (see Figure A on the left) by predicting the domain identity from the inputs.
2. **Computing domain prototypes**: We average features from each domain to create the prototype $\Theta(D)$ for the training domain $D$.
3. **Learning an adaptive classifier**: Next we learn the adaptive classifier $F$ over the input $(x, \varphi(D))$ that predicts the label $y$.

At test time, we use the first network to compute the domain prototype $\Theta(D)$ for each test domain $D$ and predict using $F$.

- Is this transductive learning? No!
  - We do not assume knowledge of the test set in advance. Furthermore, we can do inference on each sample individually.
  - Is this incompatible with domain-invariant approaches? No!
    - We simply account for the domain information in the classifier. $F$ can involve domain-invariant representation learning to improve performance, given the knowledge of the embedding (future work).
- Is this approach consistent? Yes!
  - (Convergence of $\varphi(D)$): Under suitable regularity assumptions, the empirical $\varphi(D)$ converges to the true embedding at a rate of $O(1/n^2)$.
  - (Generalization Error): The excess risk for a class $f$...diminishes at a rate of $\frac{\log N}{N} + \frac{1}{\sqrt{N}}$.

The GeoYFCC Dataset

GeoYFCC has 40 training, 7 validation and 15 test domains, with an overall 1.1M images and 1261 classes, and exhibits:
- domain shift, label shift, and long-tailed class distributions.