Metalearning

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Outline

Learning Objectives

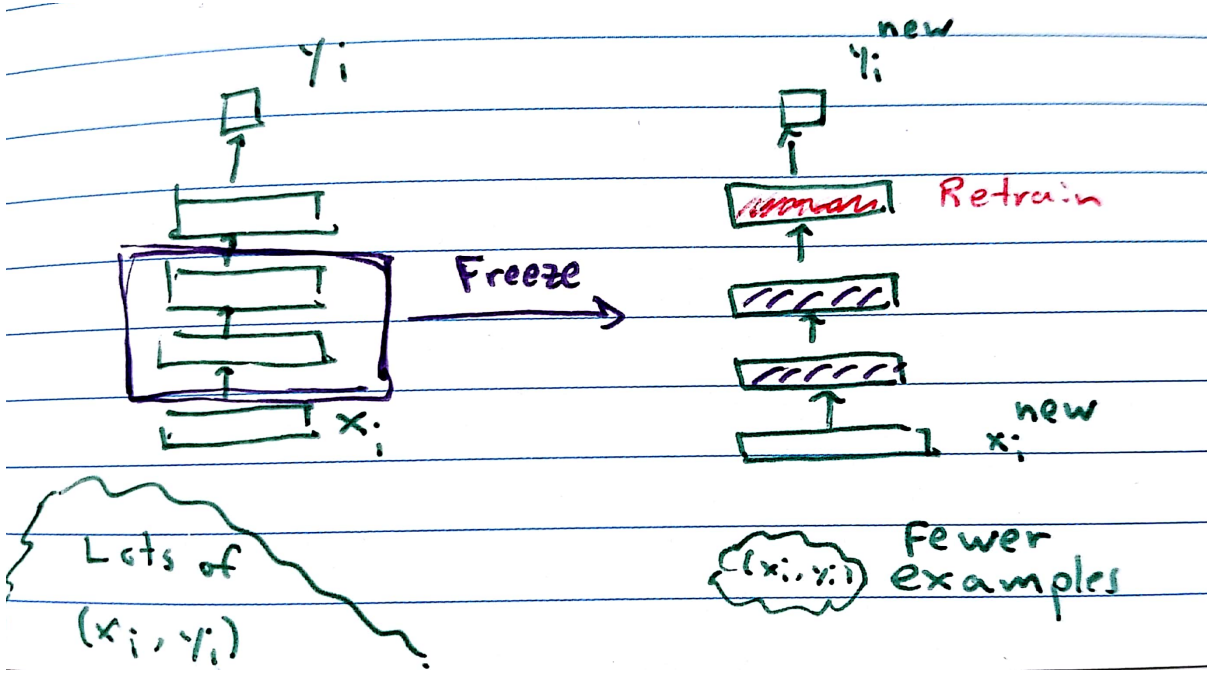
- Understand basic metalearning setup
- Recognize metalearning problems "in the wild"
- Understand foundational algorithms, on which the rest the field stands

Challenge

- Deep learning methods need lots of data
- Humans don't need a million examples of Yaks to be able to recognize a new one
- How can we have our machines learn from fewer examples?

Transfer Learning

- People figured out a while ago that you can *transfer* to small data settings
- Train deep model one big dataset, then fine tune the top layers
- Bottom layers learn generic visual features



Connection to Real-World

- Different users of an app
- Different regions of satellite imagery
- Different hospital databases

Transfer Learning

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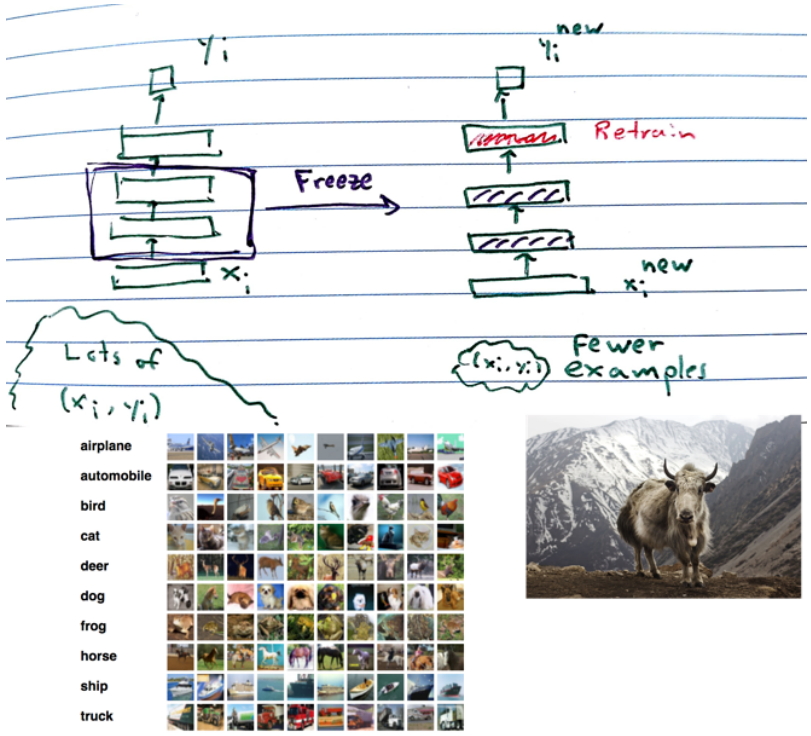

Transfer Learning

- People figured out a while ago that you can *transfer* to small data settings
- Train deep model one big dataset, then fine tune top layers to scarce samples
- Bottom layers learn generic visual features

```
# Get pretrained model and freeze
model_conv = torchvision.models.resnet18(pretrained=True)
for param in model_conv.parameters():
    param.requires_grad = False

# New top layer parameters
num_ftrs = model_conv.fc.in_features
model_conv.fc = nn.Linear(num_ftrs, 2)
```

Figure: From the pytorch transfer learning tutorial

- The same underlying features seem useful across a lot of tasks...
- Transfer learning is nice, but requires lots of hand-tuning
- Can we learn models that automatically adapt in scarce data settings?

Metalearning Setup

- Forget about solutions for now, how should we formulate the problem?
- Create many small train / test datasets (calls these "episodes")
- Same classes don't have to appear in each episode
- Metalearner maps new datasets to new (hopefully adapted) algorithm

Metalearning Setup

- Metalearner maps new datasets to new (hopefully adapted) algorithm
- Usual training / testing is like
  - $D_{\text{train}} = (x_i, y_i)_{i=1}^{n}$
  - $D_{\text{test}} = (x_i, y_i)_{i=1}^{n'}$
- New training / testing is like
  - $D_{\text{metatrain}} = \{D_{\text{train}}^{n}, D_{\text{test}}^{n}\}_{n=1}^{N}$
  - $D_{\text{metatest}} = \{D_{\text{train}}^{n}, D_{\text{test}}^{n}\}_{n=1}^{N'}$
- You don't have to fine-tune to each training / testing episode!

Metalearning Setup (picture)

- Given a new user, domain, etc $\rightarrow$ return a new algorithm
- Hope that you can share information across users / domains

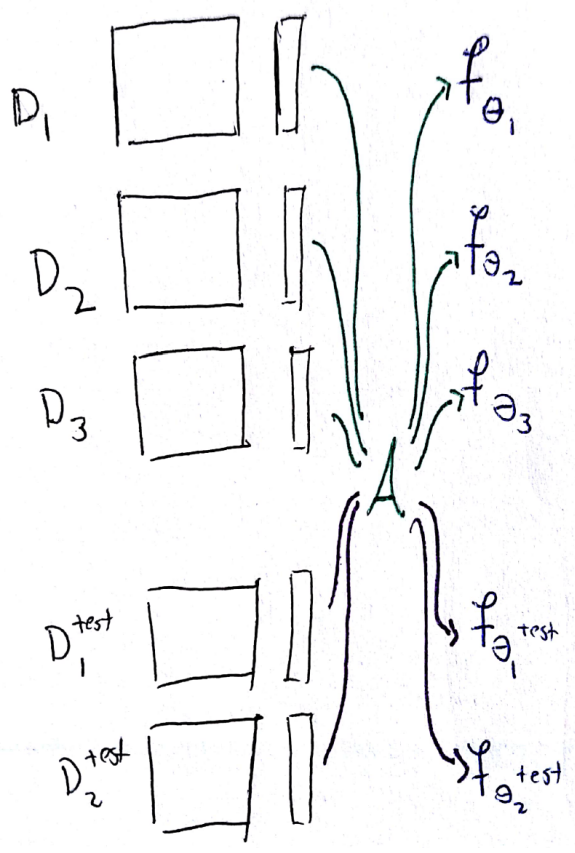

Figure:

Metalearning Setup (picture)

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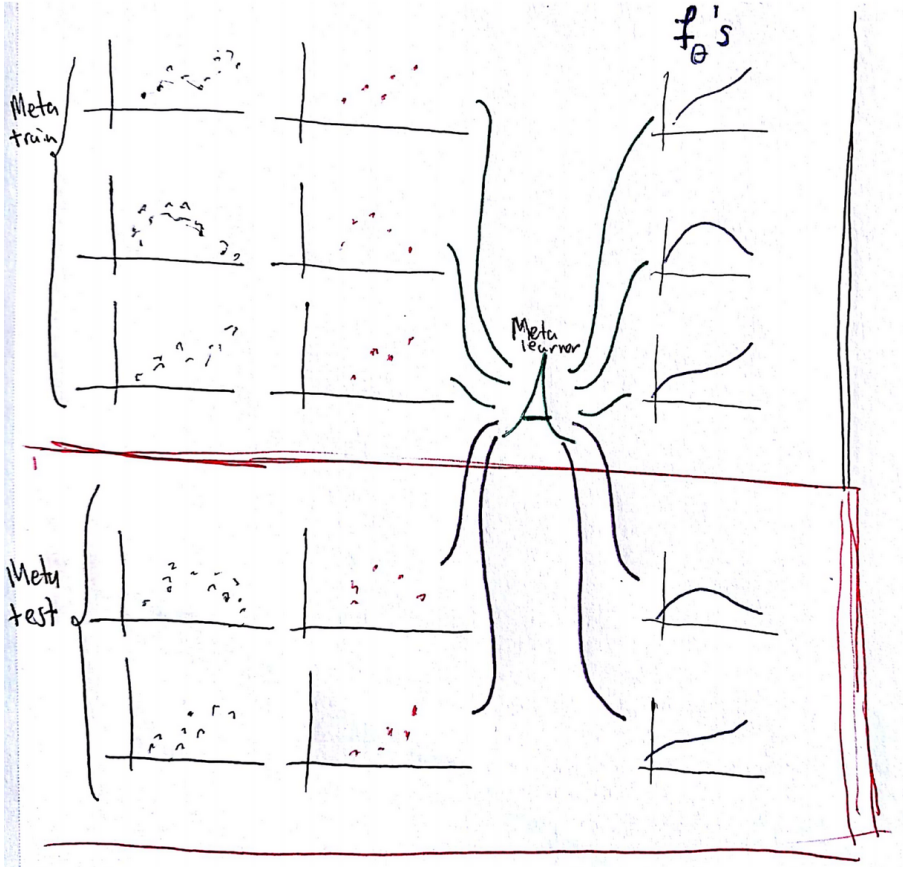

Figure:

Discussion

Brainstorm some problems or application areas where metalearning might be useful?

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Brainstorm some problems or application areas where metalearning might be useful?

- "Training Medical Image Analysis Systems like Radiologists"
- Pest detection across types of crops
- Satellite imagery analysis across diverse environments

How to do this?

- **Idea 1**: Draw inspiration from existing algorithms that can adapt to new classes
- **Idea 2**: Learn a global model that can be "perturbed" to work in many different domains

How to do this?

- **Idea 1**: Draw inspiration from existing algorithms that can adapt to new classes
  - Nearest Neighbors
  - Prototype methods
- **Idea 2**: Learn a global model that can be "perturbed" to work in many different domains
  - Like hierarchical / empirical bayesian models

Outline

Nearest Neighbors

- Nearest neighbors knows how to handle new classes (e.g., Yaks)
- Key is that it has a distance between all examples

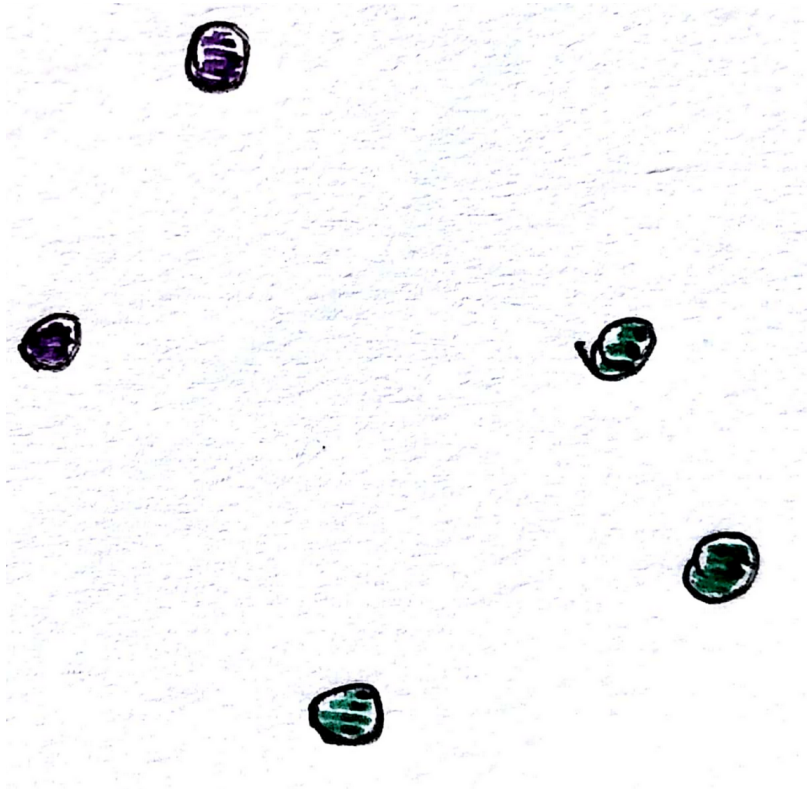

Figure: The original data, just two classes.

Nearest Neighbors

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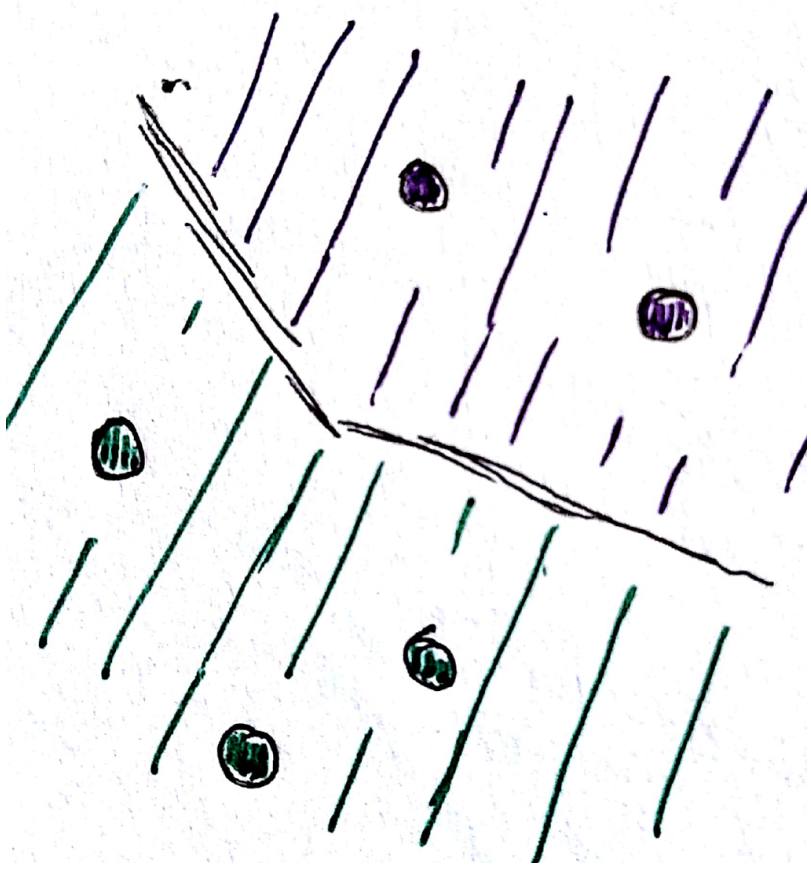

Figure: Can draw the decision boundary between two classes.

Nearest Neighbors

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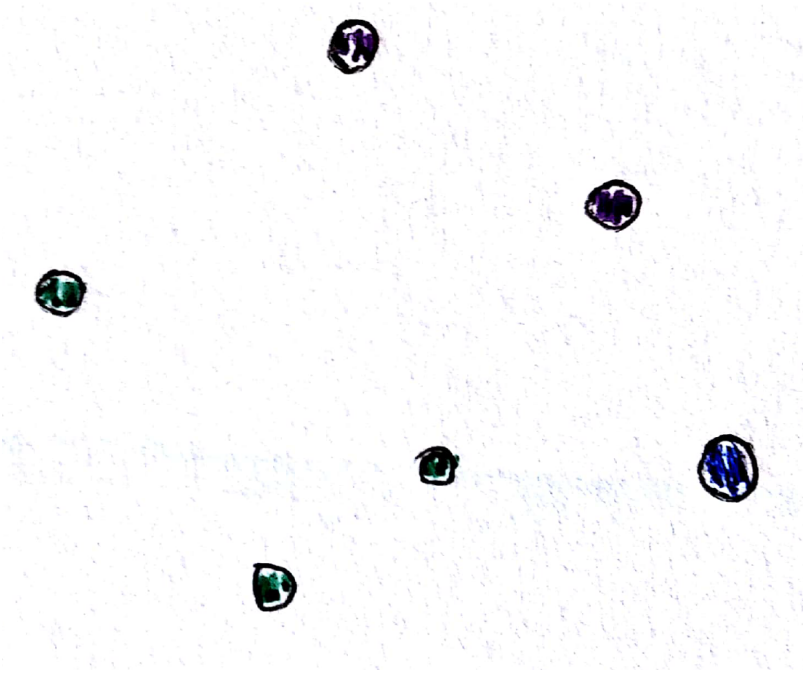

Figure: What if we see a third class?

Nearest Neighbors

- Nearest neighbors knows how to handle new classes (e.g., yaks)
- Key is that it has a distance between all examples

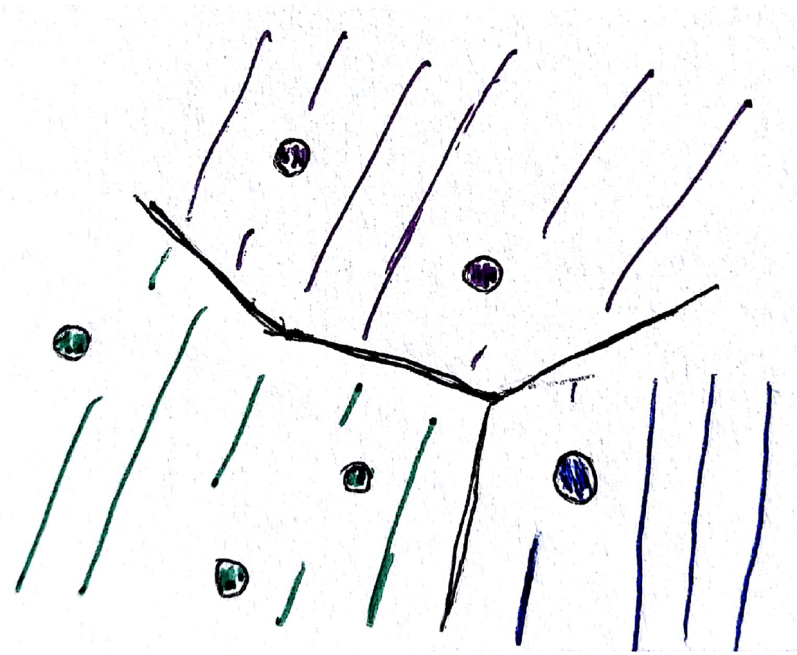

Figure: Just introduce new decision boundaries.

Nearest Neighbors (Sharing Information)

- If we run nearest neighbors separately on each task, we aren't sharing any information
- We want to use information we learned from data with horses to be able to classify yaks.
- Idea: Learn a good cross-task representation.

Smoothing Nearest Neighbors

- To learn shared representation, we to use deep learning
- But nearest neighbors is not differentiable! Can't use backprop.
- Idea: Smooth nearest neighbors

Smoothing Nearest Neighbors

- Idea: Smooth nearest neighbors

$$\hat{y}(x) = y_i \mathbb{I}(N(x) = x_i) \tag{1}$$

$$= \sum_{j=1}^{n} y_j a(x, x_j) \tag{2}$$

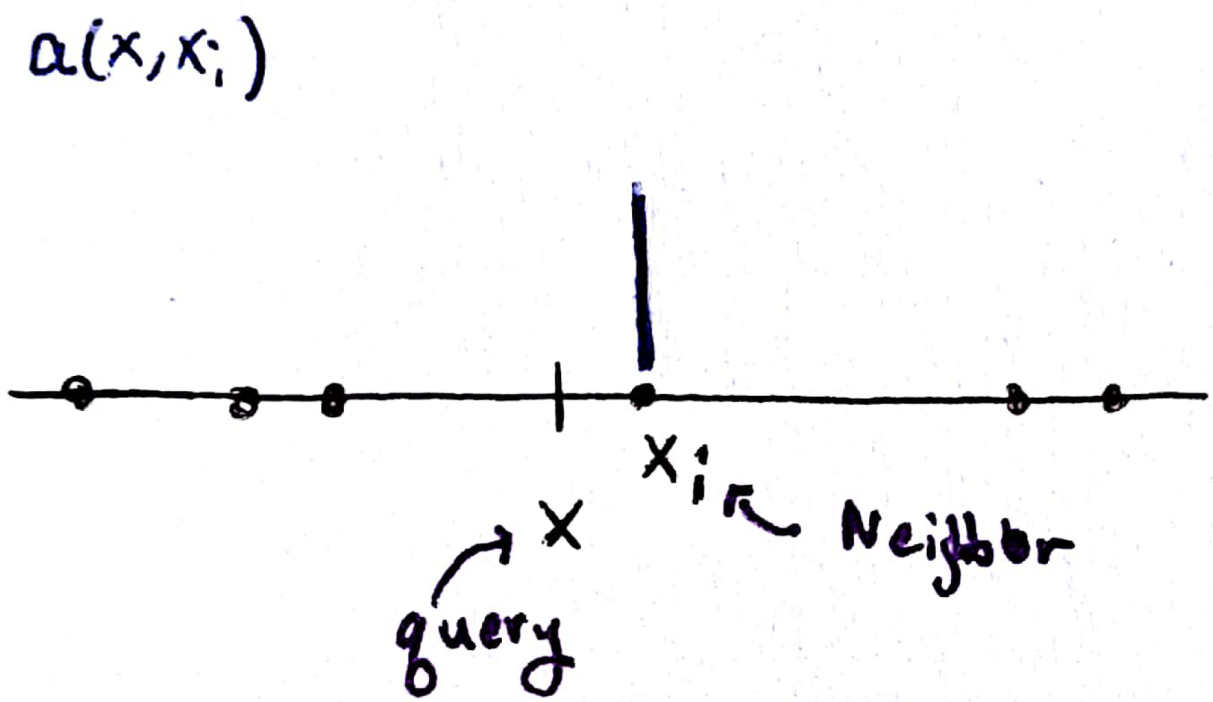

Figure: Nearest neighbors bases its prediction entirely on the nearest neighbor.

Smoothing Nearest Neighbors

- Idea: Smooth nearest neighbors

$$\hat{y}(x) \approx \sum_{j=1}^{n} y_j \tilde{a}(x, x_j) \tag{3}$$

$$\tilde{a}(x, x_i) := \frac{\exp(-d(x, x_i))}{\sum_{j=1}^{n} \exp(-d(x, x_j))} \tag{4}$$

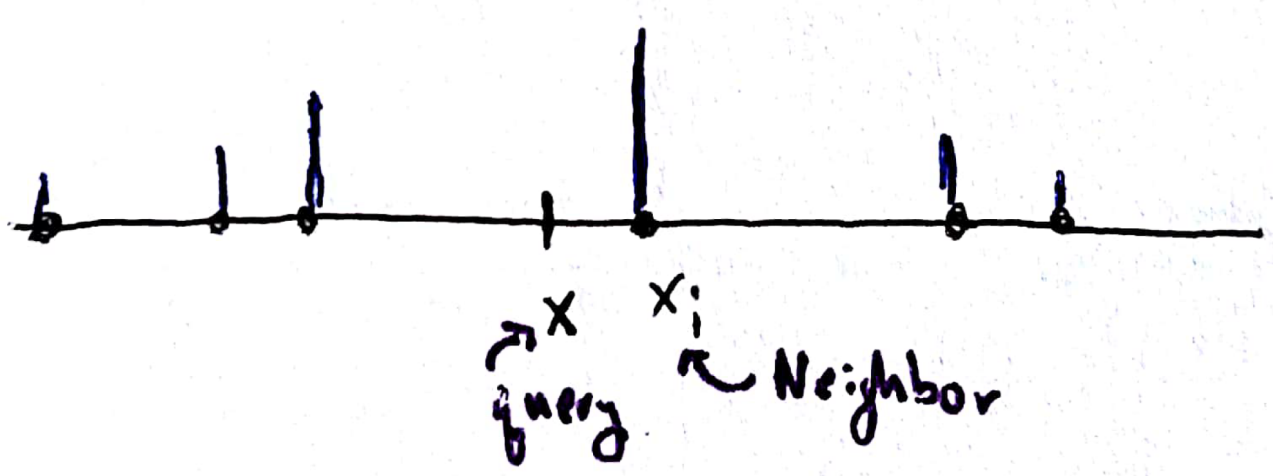

Figure: We can smooth this out by allowing contributions that decay with distance.

Discussion

- For k-Nearest Neighbors, larger k reduces variance but increases bias
- k controls model complexity
- How do we control complexity in this algorithm?

Shared Embeddings

- How to share representations across tasks?
- Learn shared embedding functions: $x \rightarrow g_{\varphi}(x)$

Overall Process

- Across all the tasks, learn a common embedding
- Task-specific nearest neighbors classifiers (since task-specific classes)
- Since function $a(x, x_i)$ is smooth, can backpropagate errors to learn optimal g

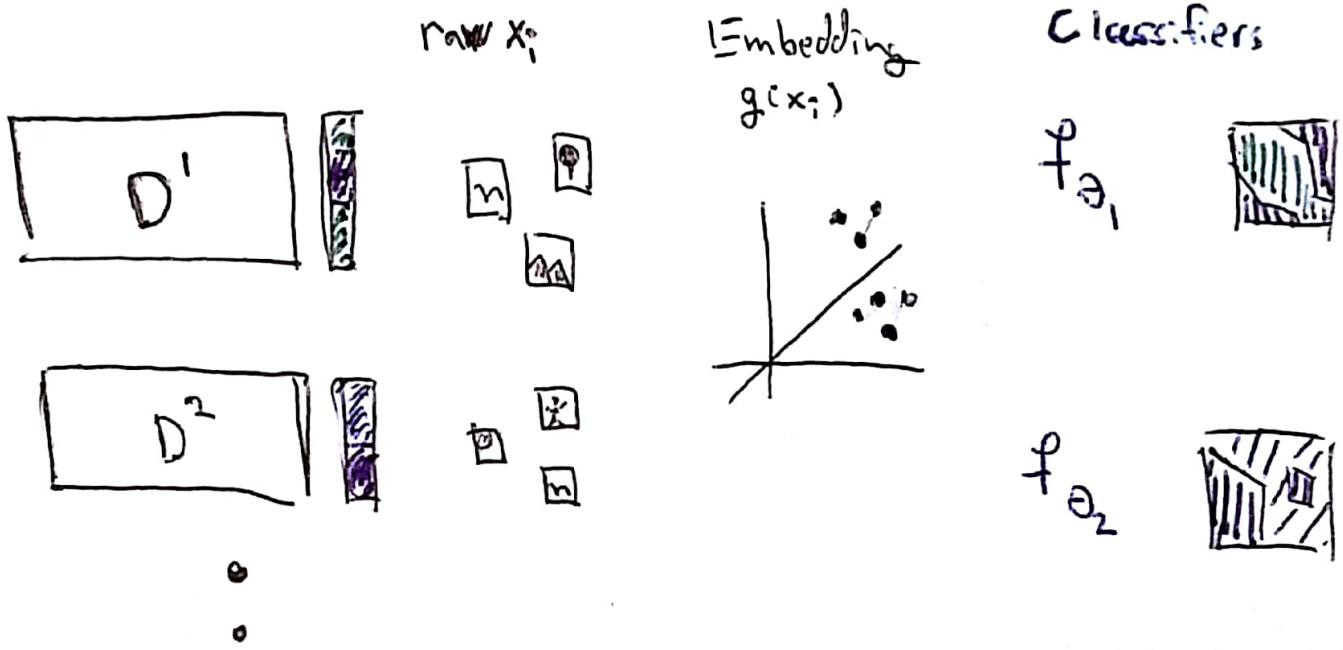

Figure: The overall process, from datasets, to shared embedding, to learned classifiers.

Prototypes

- An alternative to nearest neighbors that also works with new classes is the prototype method
- Define prototypes for each class, and assign new examples to the closest prototype

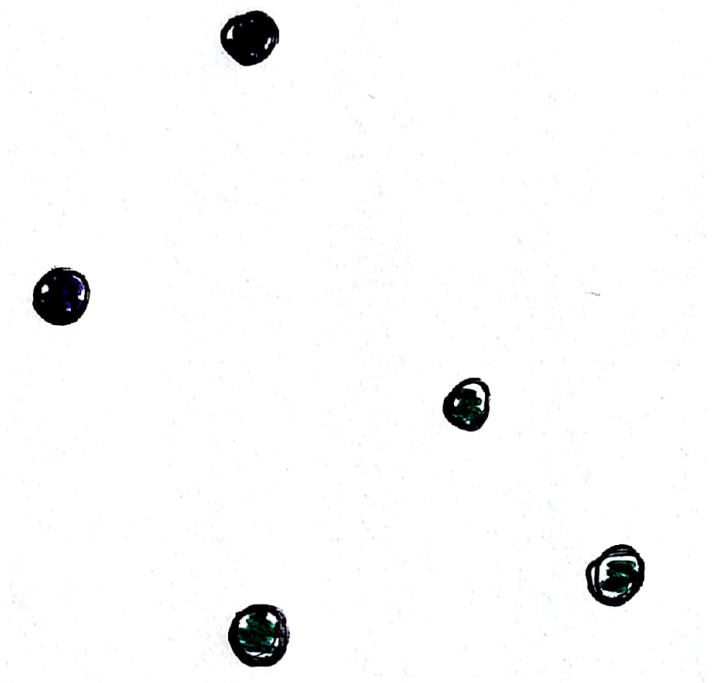

Figure: The original two class dataset.

Prototypes

- Prototypes: $c_k = \frac{1}{N_k} \sum_{i:y_i=k} x_i$

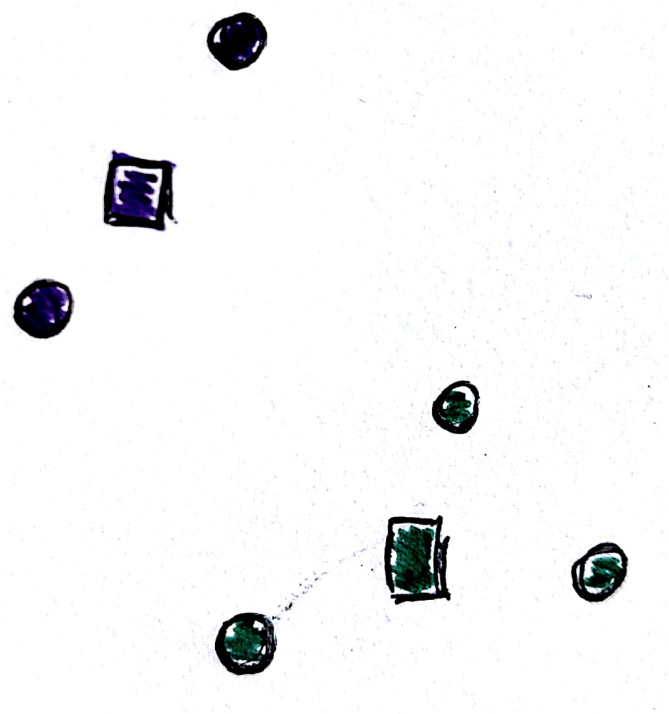

Figure: Define prototypes for each class.

Prototypes

- $\hat{y}(x) = \arg\min_{k \in \{\text{green, purple}\}} d(x, c_k)$
- If you want probabilities, $\mathbb{P}(y(x) = k | D^n) \propto \exp(-d(x, c_k))$

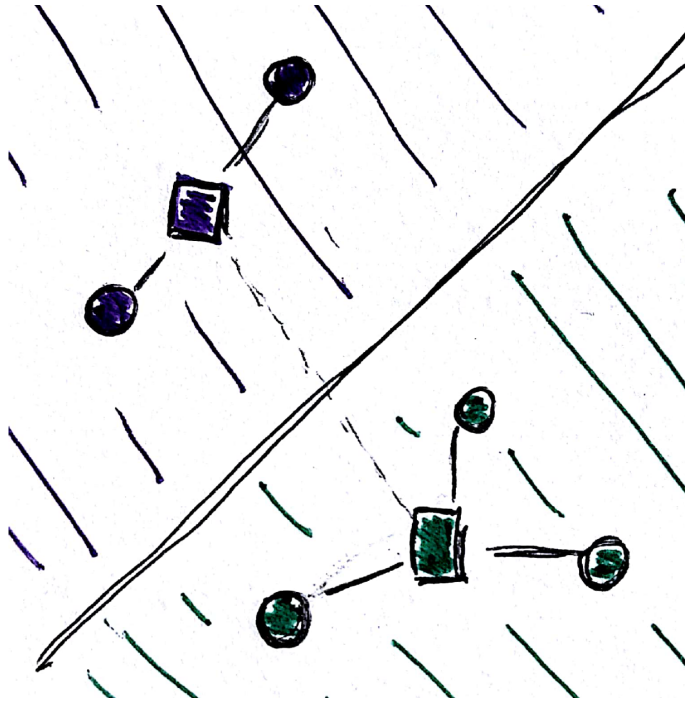

Figure: Predictions are made according to distance to the prototypes.

Prototypes

- Now we see $(x_i, y_i = \text{blue})$
- This blue class may have never appeared in any of our metatraining examples

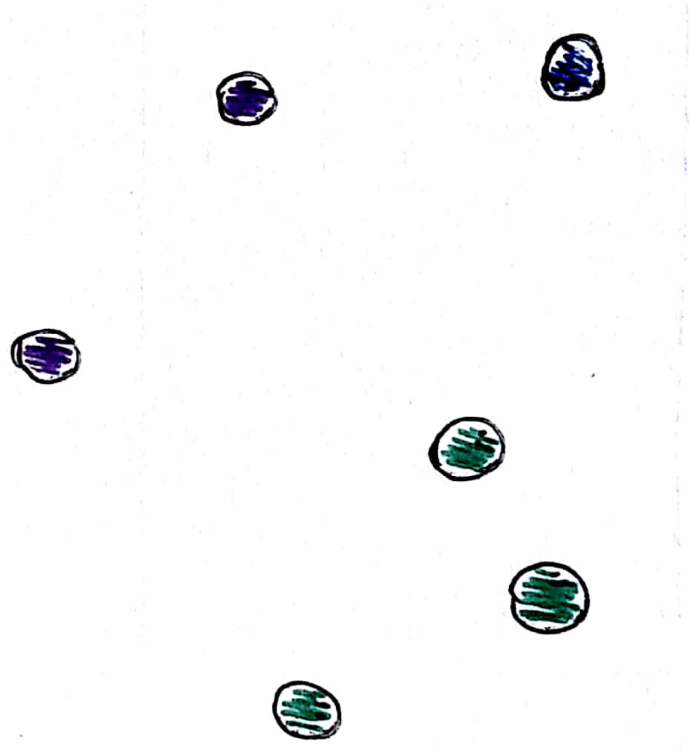

Figure: We can introduce a new class.

Prototypes

- $\hat{y}(x) = \arg\min_{k \in \{\text{green, purple, blue}\}} d(x, c_k)$
- If you want probabilities, $\mathbb{P}(y(x) = k | D^n) \propto \exp(-d(x, c_k))$

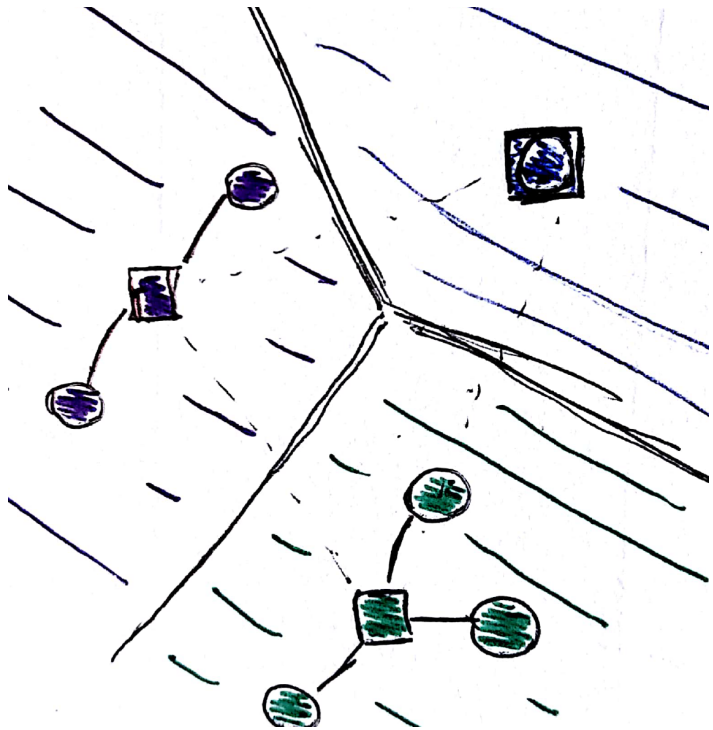

Figure: The new datapoint becomes a prototype, and we make classifications according to distance to prototypes, as before.

Prototypes: Sharing across tasks

- Sharing accomplshed through a common embedding $g_{\varphi}(x)$
- Prototypes: $c_k = \frac{1}{N_k} \sum_{i:y_i=k} f_{\varphi}(x_i)$
- $\hat{y}(x) = \arg\min_k d(f_{\varphi}(x), c_k)$
- $\mathbb{P}(\hat{y}(x) = k | D^n) \propto \exp(-d(f_{\varphi}(x), c_k))$

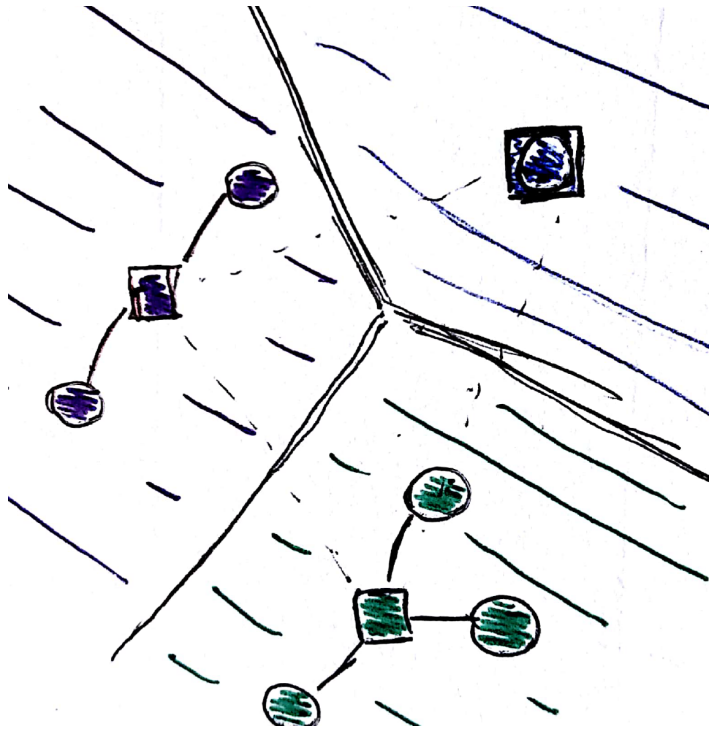

Figure: To share across tasks, we learn prototypes after embedding all points according to some shared embedding function .

Outline

Model Agnostic Meta-Learning

- Imagine that the model parameters will be similar across tasks
- Learn a global parameter and adapt it on a task-by-task basis
- (This is analogous to transfer learning)

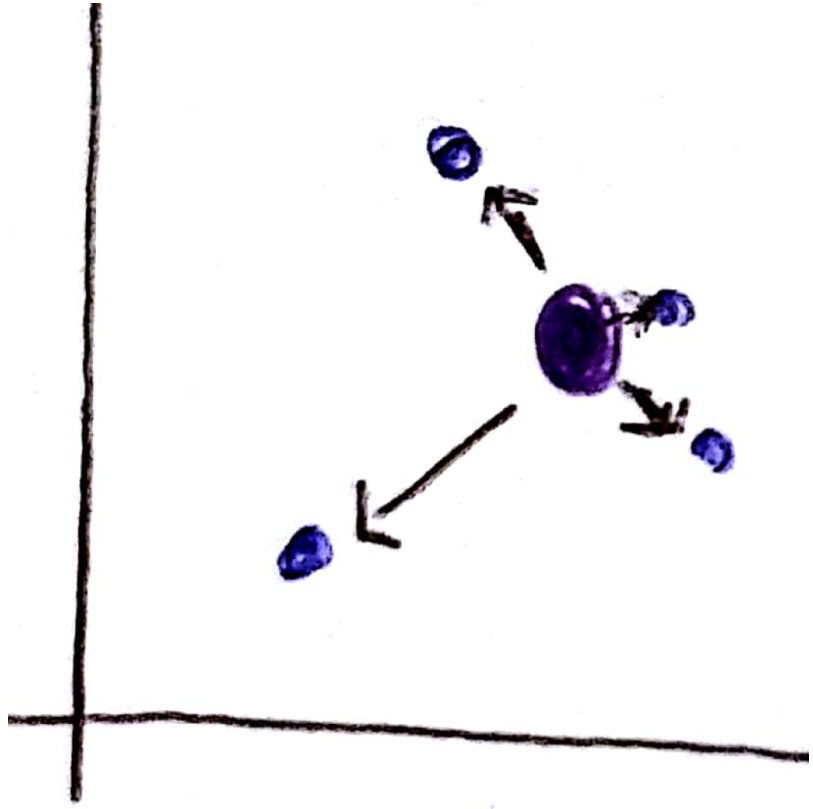

Figure: On new tasks, adapt the global parameter.

Learning Strategy

- Imagine that the model parameters will be similar across tasks
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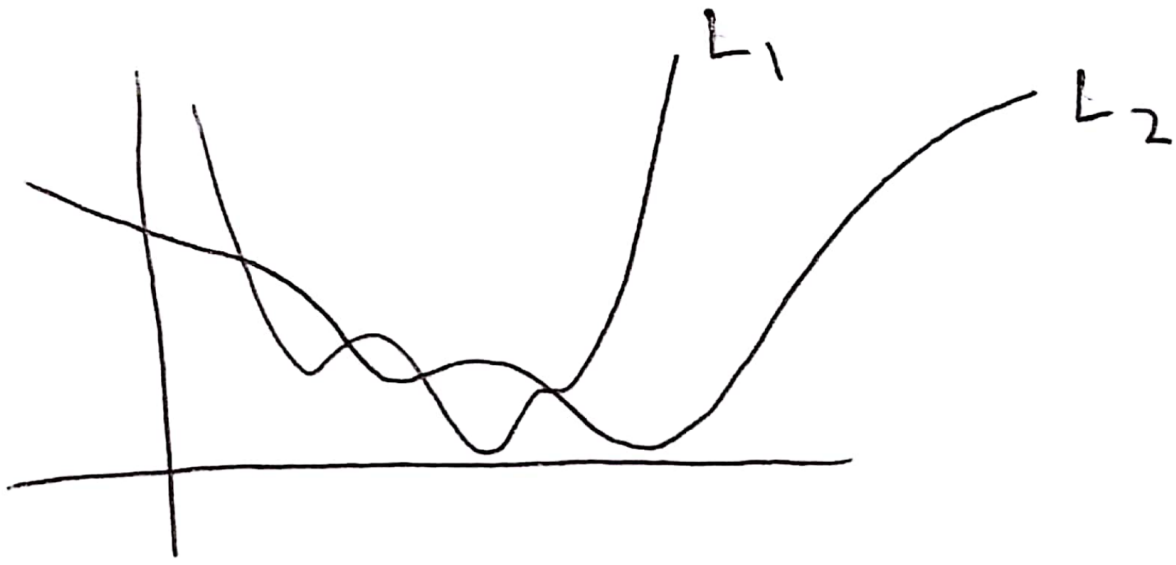

Figure: Each task has it's own loss landscape over Θ.

Learning Strategy

- Imagine that the model parameters will be similar across tasks
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- (This is analogous to transfer learning)

Figure: We start with some guess at a global θ.

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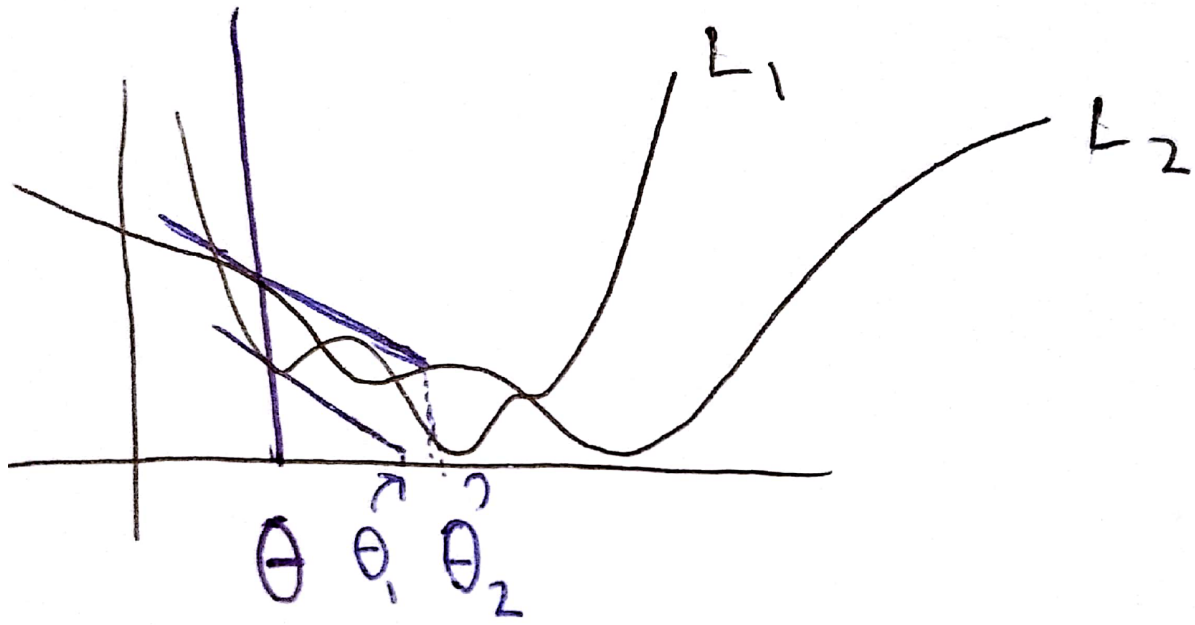

Figure: We find task-specific θ_i's by taking a step from this global θ.

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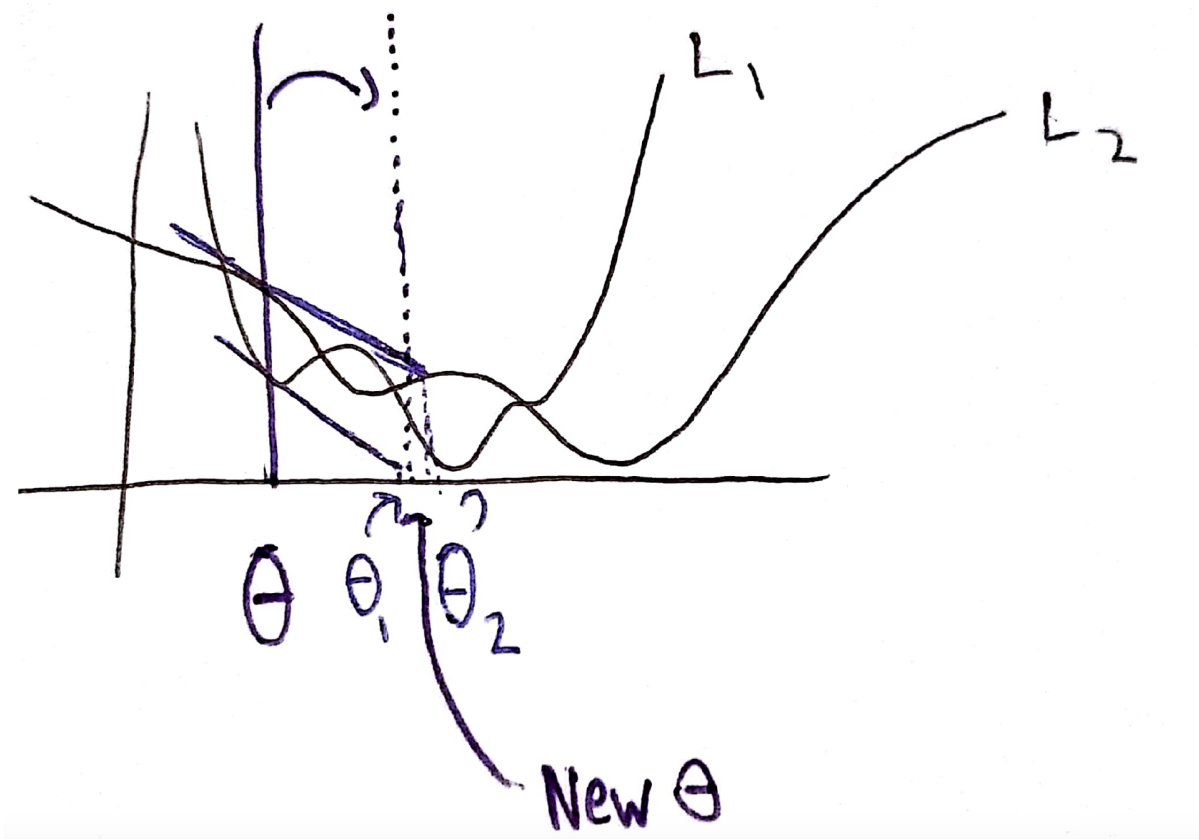

Figure: We update the global θ according to the averarge direction across all the tasks.

Learning Strategy

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Algorithm 2 MAML for Few-Shot Supervised Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
4: **for all** $\mathcal{T}_i$ **do**
5: Sample K datapoints $\mathcal{D} = \{\mathbf{x}^{(j)}, \mathbf{y}^{(j)}\}$ from $\mathcal{T}_i$
6: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ using $\mathcal{D}$ and $\mathcal{L}_{\mathcal{T}_i}$ in Equation (2) or (3)
7: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
8: Sample datapoints $\mathcal{D}_i' = \{\mathbf{x}^{(j)}, \mathbf{y}^{(j)}\}$ from $\mathcal{T}_i$ for the meta-update
9: **end for**
10: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$ using each $\mathcal{D}_i'$ and $\mathcal{L}_{\mathcal{T}_i}$ in Equation 2 or 3
11: **end while**

Figure: In case you are interested in hte details, check against the original paper