HIDRA: Head Initialization across Dynamic targets for Robust Architectures

Rafael Rego Drumond∗† Lukas Brinkmeyer∗† Josif Grabocka∗ Lars Schmidt-Thieme∗

Abstract
The performance of gradient-based optimization strategies depends heavily on the initial weights of the parametric model. Recent works show that there exist weight initializations from which optimization procedures can find the task-specific parameters faster than from uniformly random initializations, and that such a weight initialization can be learned by optimizing a specific model architecture across similar tasks via MAML (Model-Agnostic Meta-Learning). Current methods are limited to populations of classification tasks that share the same number of classes due to the static model architectures used during meta-learning. In this paper, we present HIDRA, a meta-learning approach that enables training and evaluating across tasks with any number of target variables. We show that Model-Agnostic Meta-Learning trains a distribution for all the neurons in the output layer and a specific weight initialization for the ones in the hidden layers. Hydra explores this by learning one master neuron which is used to initialize any number of output neurons for a new task. Extensive experiments on the Miniimagenet and Omniglot data sets demonstrate that HIDRA improves over standard approaches while generalizing to tasks with any number of target variables. Moreover, our approach is shown to robustify low-capacity models in learning across complex tasks with a high number of classes for which regular MAML fails to learn any feasible initialization.

1 Introduction
Machine learning models and especially deep neural networks are crucial in various fields of research and industry to the point that not only experts, but also practitioners of related areas are dependent on their application. In almost all cases, the optimization of these parametric models relies on a suitable selection of multiple hyperparameters which influence the training performance drastically. This parameter selection either requires expert knowledge or the use of hyperparameter optimization techniques [18]. One often disregarded hyperparameter is the weight initialization for parametric models which is required as a starting point for gradient-based-optimization. A suitable weight initialization is essential for a fast convergence to a near-optimal solution when using a method that generally converges to a local optima. Standard hyperparameter optimization approaches are not capable of finding a per-weight initialization for neural networks due to their high number of continuous weight parameters. Instead, a random weight-initialization is typically chosen as a starting point [5, 7].

Recent approaches such as MAML [2] show that it is possible to learn a weight initialization for a specific neural network by utilizing second-order optimization for training across a set of similar tasks. This allows to find a per-weight initialization that can lead to a fast convergence for similar tasks. However, such a process requires that each task has the same number of target variables since a specific model architecture is optimized which also means having a fixed number of output neurons. In practice it results in a huge
computational effort since it is necessary to optimize a single model architecture for each potential number of output neurons expected during application. Moreover, the initialization should perform equally well for two identical tasks with permuted class-order due to the fact that there is no inherent sequence to the target variables of a standard classification task. This suggests that the different output neurons cannot learn different output weights when trained across data sets with different class semantics. We propose an extension to existing meta-learning approaches by learning a single master neuron which can be used to initialize any number of output neurons. During meta-learning, it is used to initialize the required number of output neurons for a specific task, train on the task via MAML and update the master neuron with regard to the different output neurons. Thus, enabling approaches like MAML to train and evaluate across tasks with a dynamic number of target variables.

The core contributions of this work are as follows: (1) We demonstrate that standard MAML learns indifferent output neurons which limits the approach to a fixed number of target variables. (2) We extend MAML to work across dynamic target sizes by deploying a general master neuron that learns to initialize any number of output neurons for similar tasks. (3) Finally, we show that our method HIDRA leads to a higher model robustness such that even for tasks with a high number of target variables, finding a suitable weight initialization is feasible while regular MAML fails to do so (Figure 1).

2 Related Work

Current meta-learning approaches that find a model-weight initialization are typically evaluated by applying them to few-shot classification problems, because it is generally easier to generate the necessary number of tasks required for meta-learning when dealing with few-shot tasks. Few-shot learning [6, 21, 14] strives to achieve the highest possible classification performance when faced with a new task that comprises only a handful of samples per class. This can be achieved by learning an initialization that converges fast, even when only few instances are given, but also through the application of other meta-learning approaches. For example, Liu et al. [11] try to deal with this low-data regime by classify all available tasks in one step by using transductive inference through label propagation as opposed to having a model that processes single tasks. Snell et al. [19] propose to learn a single model via meta-learning that embeds instances of a task in a metric space to measure the distances between them. For a novel task, a prototypical representation is selected for each target class to predict new images simply by looking at the nearest neighbor among these prototypes. To better calculate these distances, Oreshkin et al. devised TADAM [13], a relation metric that adapts based on the task and scales appropriately as well.

In contrast to these methods, there are many approaches that strive to optimize the model on the training instances of the evaluation task, instead of simply using them for inference. Training a model on a single few-shot task with such a small number of samples requires a suitable model initialization because it can very easily converge to a poor local optima otherwise.

Another category of meta-learning approaches is referred to as Transfer Learning [20, 14]. It describes the process of training a model on different auxiliary tasks and then using the learned model to actually fit to the target problem to improve performance. For instance, pre-training blocks of convolutional neural networks on smaller tasks allows fitting a joint model to a much larger task [29]. Another angle of transfer learning is using auxiliary tasks to help the model extract more useful features by training extra heads of the architecture to learn metadata from the same inputs [13].

Our work builds on the research of Finn et al. Model Agnostic Meta-Learning (MAML) [2] finds an initialization for a specific model M by training it across a set of similar few-shot learning tasks. They optimize a single model initialization \( \theta^* \) by taking into account the validations loss after some iterations on each task after starting on this same initial point. Every task consists of pairs of inputs and target values. This means the authors sample a batch of tasks \( \tau \) from a greater set \( \mathcal{T} \). New parameters \( \theta'_\tau \) are then calculated for a task \( \tau \) after performing one or more update steps using the specific loss \( L_\tau \) starting with the initialization \( \theta^* \). For the update steps, after initializing \( \theta'_\tau \leftarrow \theta^* \), this can be written as:

\[
(2.1) \quad \theta'_\tau \leftarrow \theta'_\tau - \alpha \nabla_{\theta'_\tau} L_{\tau}^{\text{train}}(M_{\theta'_\tau})
\]

Then \( \theta^* \) is updated using the second derivative of the updated weights with regard to their validation performance over all tasks in the meta-batch \( \tau \) as in:

\[
(2.2) \quad \theta^* \leftarrow \theta^* - \beta \frac{1}{|\mathcal{T}|} \sum_{\tau} L_{\tau}^{\text{val}}(M_{\theta'_\tau})
\]

MAML can be applied to any architecture, but out-of-the-box will only work on a fixed topology. Alex Nichol et al. developed REPTILE [12] in order to simplify the heavy computation of second derivatives from MAML by approximating Equation (2.2) as:

\[
(2.3) \quad \theta^* \leftarrow \theta^* - \beta \frac{1}{|\mathcal{T}|} \sum_{\tau} (\theta'_\tau - \theta^*)
\]
Finn et al. later expands this work with Probabilistic Model-Agnostic Meta-Learning [3] to learn a distribution for the model parameters by injecting Gaussian noise into the gradient descent steps. Inspired by maml, a recent paper by Rusu et al. called LEO [17] proposes a method to sample network parameters of a model for few-shot learning. An additional encoder network takes a task as input and generates a latent embedding that consists of a mean and a standard deviation for each neuron to initialize. These distributions are used to sample the parameters for the respective neurons. During the training process the latent representation is updated instead of the weights itself. They show the effectiveness of that approach by achieving state-of-the-art results for few-shot-classification. The complexity of the generated latent embedding depends on the number of neurons to initialize since the approach generates a weight distribution to sample from for each neuron. Due to this computational bottleneck, the authors only generate the weights for an output layer that is placed on top of a pre-trained deep residual network which is used to generate task-embeddings that facilitate learning.

So far, none of these methods are specifically designed to work across tasks with different input and target shapes. The work by Brinkmeyer and Drumond et al., CHAMELEON [11], targets the problem of meta-learning tasks having a variable input schema. The authors train a network which transforms different input schema of training batches to a fixed representation, enabling meta-learning methods such as REPTILE to work with tasks with different input sizes by attaching this model to the target network’s input layer. Similarly Dataset2Vec from Jomaa et al. [8] extracts useful meta-features from different data sets to perform hyperparameter optimization.

Our work focuses on meta-learning over tasks with different target variables, being the first to our knowledge to directly explore such a problem.

3 Methodology

Meta-learning approaches like maml train a parameter initialization $\theta^*$ for a specific model $M$ by sampling meta-batches of similar tasks $\tau$ from a set of tasks $\mathcal{T}$. In few-shot classification, a task $\tau$ is represented by a single batch containing $K$ instances for each of the $N$ classes present. Thus, it consists of predictor data $X_\tau$ and target data $Y_\tau$. Typically, similar tasks are defined to have the same feature space but different target variables such that $X_\tau \in \mathbb{R}^{NK \times F}$ and $Y_\tau \in \mathbb{R}^{NK \times N}$ with $F$ features for every task $\tau \in \mathcal{T}$. As usually defined in the literature, this type of problem setting is referred to as $N$-way-$K$-shot. Thus, the goal is to provide a task with $K$ instances for each of the selected $N$ classes to the model and observe a high accuracy on unseen instances of that task after training. Furthermore, a task $\tau$ comes with a predefined training/test split $(X_\tau^{\text{train}}, Y_\tau^{\text{train}}, X_\tau^{\text{test}}, Y_\tau^{\text{test}})$.

Most optimization-based meta-learning approaches operate in two phases: An inner loop and an outer loop. During the inner loop, the model $M$ is trained on a specific task starting from the current weight initialization $\theta^*$ for $U$ gradient steps. The updated parameter set $\theta'$ for a task $\tau$ is then given by:

$$\begin{align*}
\theta'_\tau &= G(M, \theta^*, \text{steps}, X_\tau^{\text{train}}, Y_\tau^{\text{train}})
\end{align*}$$

where $G$ is the optimization method used to compute the new weights by performing a number of inner update steps. For maml, this is shown in Equation 2.1. Afterwards, the performance of the current initialization is evaluated by measuring the validation performance for the same task with those updated weights. The outer loop executes the inner loop for a batch of tasks to update the current initialization $\theta^*$ with respect to the validation performance. The outer meta-objective is then defined as:

$$\begin{align*}
\min_{\theta^*} &\mathbb{E}_{\tau \sim \mathcal{T}} \mathcal{L}_{\text{val}}(X_\tau^{\text{test}}, Y_\tau^{\text{test}}, M, \theta'_\tau)
\end{align*}$$

In maml this outer objective is optimized by relying on the second derivatives as described in Equation 2.2.

Optimizing a fixed network architecture restricts the model $M$ to tasks with the same number of classes. As already stated previously, the learned initialization is required to be invariant to permutations of the class order since two sampled tasks could have the same instances $X$ while having their classes $Y$ in a different order. This means, that there should be no inherent difference between the initialization learned for the different output neurons. At the same time, few-shot classification is always evaluated with unseen classes. Thus, it should be possible to learn a single output neuron initialization in the outer loop that can be dynamically adapted to each number of classes in the inner loop.

3.1 HIDRA Our method learns a single output neuron as the master node $\phi$ which is replicated $c$ times during the inner-loop for a task with $c$ classes. HIDRA takes into consideration that in every task the number of classes might vary. Even when two tasks have the same amount of target variables, their labels may represent different classes. In essence we need to find a dynamic architecture that works for any number of target variables while the initialization performs equally well for any label. In order to do so, we create the master node $\phi$. When $\phi$ is replicated $c$ times it creates the output layer for a task that predicts $c$ number of values. This setup is illustrated in Figure 2.

Given a network architecture $M(x)$ with initial parameters $\theta^*_M$, we first randomly initialize the master
The full approach is depicted in Algorithm 1, showing the inner and outer loop of HIDRA.

Algorithm 1 HIDRA Method
1: Select gradient step-sizes $\alpha$ and $\beta$
2: Initialize Meta-Data-Set $\mathcal{T}$
3: Initialize Model $M(x)$ with $\theta_M$
4: Initialize Output Master Node $\phi$
5: for Max-Iterations do
6: Sample batch $b$ of tasks $\tau$ from $\mathcal{T}$ with a random output size $c_b \sim \mathbb{N}$
7: Instantiate output layer $\Psi_b$ with $c_b$ neurons
8: for every neuron $\psi_k \in \Psi_b$ do
9: $\psi_k \leftarrow \phi$
10: end for
11: Define network $M_{\psi_b}(x) := \Psi_b(M(x))$
12: $\theta_b = [\theta_M, \Psi_b]$
13: for every task $\tau \in b$ do
14: $\theta^*_\tau \leftarrow \theta_b$
15: for $n$ amount of inner steps do
16: $\theta^*_\tau \leftarrow \theta^*_\tau - \alpha \nabla \theta_b \mathcal{L}^{val}(M_{\psi_b}, \theta^*_\tau)$
17: end for
18: end for
19: $\theta_b \leftarrow \theta_b - \beta \frac{1}{|\mathcal{T}|} \nabla \theta_b \sum_{\tau} \mathcal{L}^{val}(M_{\psi_b}, \theta^*_\tau)$
20: $\phi = \frac{1}{C} \sum_{\psi} \psi$
21: end for

4 Experiments
We conduct experiments on the standard few-shot classification data sets Omniglot [10] and Miniimagenet [10]. Both are frequently used as few-shot classification benchmarks. Omniglot consists of 1623 written characters, each with 20 instances, taken from 50 different alphabets. We randomly split the data set with 1200 characters used for training and the rest for testing. The Miniimagenet

Figure 2: HIDRA utilizes a fixed Model $M$ but instead of a fixed output layer, the method keeps a single neuron $\phi$ parameterized with $\theta_\phi$. Given a task $\tau$ with $C$ target variables, $\phi$ is replicated $C$ times forming a task specific output layer $\Psi$ with neurons $\psi_d$ parameterized with $\theta_{\psi_d}$. Dashed lines represent weights assigned to the master node with respect to the latent features from $M$. Dotted lines represent the master node replicating itself and its weights to create the output layer neurons.
data set includes 100 classes from ImageNet with 600 instances per class. We utilize the proposed split with 64 classes in the training, 16 in the validation and 20 in the test data set as proposed by Ravi et al. [16].

For all experiments, the same model architecture, originally proposed by [22], and the same hyperparameters are used as in [2]. It consists of four convolutional blocks, each being a 3x3 convolution, followed by batch normalization, ReLU nonlinearity and 2x2 max pooling. For Omniglot the filter size is set to 64 and for Miniimagenet to 32. The inner learning rate $\alpha$ for training the model on a specific task is set to 0.01 and 0.4 for Miniimagenet and Omniglot respectively. The meta-objective in Equation 3.5, the Adam optimizer [9] is used with a learning rate $\beta = 1e^{-3}$. Our work focuses on $N$-way 5-shot classification tasks since this work focuses on analyzing varying class numbers. As for training, the number of inner gradient steps on a task is set to 5 and 1 for training Miniimagenet and Omniglot respectively. Furthermore, for every meta-epoch we sample 32 tasks for Omniglot and 4 for Miniiimagenet. In contrast to the work of Finn et al. [2], we conducted the Omniglot experiments without data augmentation for MAML and HIDRA which leads to a slightly lower accuracy but faster runtime to evaluate all the different number of classes. For evaluation, we aggregate the accuracy across 4000 randomly sampled test tasks, performing up to 10 gradients steps for Miniimagenet and accordingly up to 3 gradient steps for Omniglot on the learned initialization. We had to use an alternative implementation of MAML due to hardware scalability problems of the original implementation when evaluating tasks with a high number of classes. Running the original code for 2 to 6 classes per task leads to an approximately $5 - 6\%$ higher accuracy compared to the results reported in this work. Since we built HIDRA on top of the same framework, we can assume that these findings transfer to other meta-learning approaches used for model initialization, including MAML.

4.1 MAML In our first experiment, we want to analyze the weight initializations for the output layer learned via MAML to show there is no inherent structure between the neurons to motivate the application of HIDRA. For that, we compared the performance of an initialization learned with MAML for 10-way 5-shot Omniglot with the same initialization, but one of the ten learned output neurons is used to initialize every other output neuron. The results, shown in Figure 3, illustrate that the weights learned for a single output neuron with MAML are already sufficient to initialize the complete output layer. The average accuracy across each of those initializations is 94.49%, while the standard initialization using all learned output weights achieves 94.58%. Most importantly, using a single output neuron to initialize the output layer leads to a higher performance in some of the cases. By visualizing these weights in Figure 4 one can see how the output neurons are all learning a similar pattern showing the redundancy for the weights in the output layer learned via MAML (contribution 1).

4.2 HIDRA For our main experiments, we compare the performance of HIDRA and MAML when training on Omniglot and Miniimagenet for a varying number of classes. Our experiments investigate different $N$-way 5-shot problem settings where the $N$ ranges from 2 to 10 classes for Omniglot and 2 to 15 classes for Miniimagenet. In order to compare our approach to MAML which only works with a fixed number of classes, we train and evaluate a separate model with MAML for each output size $N$ as baseline. Additionally, the performance of a standard random initialization is tracked for each class.
Figure 5: Performance comparison between MAML and HIDRA for different numbers of target variables when training on Miniimagenet. The left plot compares HIDRA trained with static number of target variables (i). The right plot compares the best result from the static experiments with dynamic experiments where we have varied sizes of target variables within a range (ii).

Figure 6: Performance comparison between MAML and HIDRA for different numbers of target variables when training on the Omniglot data set. This shows the average accuracy on tasks using each of the initializations. Each graph represent the accuracy for one amount of meta-steps. In this setup in particular we trained the HIDRA and MAML experiments with learning rate equal to 0.4.

Finally, we learn various initialization with HIDRA for two different settings: (i) with a fixed number of targets variables and (ii) with a varying number of target variables utilized during meta-learning. Every initialization learned via HIDRA is then evaluated for each of the different $N$-way settings.

4.3 Results and Discussion The results of the comparison between the different initialization learned with HIDRA on Miniimagenet and the ones learned via MAML are shown in Figure 5. Note that each data point in the graph for MAML represents a separate model trained for the respective number of classes, while each graph of the HIDRA experiments represents one model which is evaluated for every number of classes. The results for HIDRA show a similar performance as MAML for up to 6 classes per task, with the HIDRA models trained on 2-way and 10-way problems slightly outperforming MAML. Generally, all models initialized with HIDRA generalize to any number of classes during evaluation (contribution 2). The results for training on tasks with varying target size achieve the highest accuracy with a slight improvement over the HIDRA initialization trained for 2-way 5-shot classification.

Furthermore, MAML fails to generalize to unseen tasks when evaluating for more than 7 classes with 5 instances each when using the architecture described above. The performance of models initialized with
Figure 7: Performance comparison between MAML and HIDRA for different number of target variables when training on the Omniglot data set. This shows the average accuracy on tasks using each of the initializations. Each graph represent the accuracy for one amount of meta-steps. In this setup in particular we trained the HIDRA experiments with learning rate equal to 0.001. MAML uses learning rate equal to 0.4 which remains as the best value.

![Graphs showing performance comparison](image)

| Number of classes | Meta training | Meta validation |
|-------------------|---------------|-----------------|
| 2                 | 0.96          | 0.75            |
| 5                 | 0.87          | 0.65            |
| 8                 | 0.76          | 0.55            |
| 10                | 0.69          | 0.50            |
| 12                | 0.63          | 0.45            |

![Graphs showing performance comparison](image)

HIDRA, on the other hand, only decreases marginally with increasing number of classes. Moreover, meta-learning with HIDRA on tasks with a low number of classes is demonstrated to generalize to those with a high number of classes and vice versa, essentially computing a robust initialization which is independent of the number of target variables (contribution 3). The numerical results for these experiments are given in Table 1.

Experiments for evaluating our approach with varying number of gradient steps on Omniglot are displayed in Figure 6. HIDRA fails to outperform MAML with three gradient steps of size 0.4, as used in [2], but whereas MAML reaches its highest accuracy after 3 steps, HIDRA actually achieves the highest score after using a single gradient step on an unseen task. Due this faster convergence, we also evaluated HIDRA with a smaller inner learning rate of 0.01 (Figure 7) which shows the best performance on Omniglot when using 3 gradient steps. Numerical results for Omniglot are displayed in Table 2. The meta-learning progress for training HIDRA on Omniglot for different N-way 5-shot settings is illustrated in Figure 8. One can see that the gap between the training and validation error grows with the number of classes per task. The experiments were conducted
Table 1: Average accuracy for the experiments with MiniImageNet. Each Hydra X experiment (line) used X amount of labels during training and was evaluated for tasks with different target label size (columns). Hydra 2-10 and Hydra 4-6 are trained on tasks with a variable number of target variables. MAML is trained on a fixed output size and evaluated on the same target shape.

Table 2: Average accuracy for the experiments with Omniglot. Each Hydra X experiment (line) is trained with tasks containing X target variables and evaluated for tasks with different label size (columns). Hydra 5-30 is trained on tasks with a variable number of target variables. MAML is trained and evaluated on a fixed output size.

using an NVIDIA Tesla K80. Training on MiniImageNet takes approximately 3.5 hours for 2 classes and 13 hours for 10 classes for both hidra and maml. Our code is available online for reproduction purposes at: https://github.com/radrumond/hidra.

5 Conclusion

In this paper, we present a novel approach for learning a task-specific initialization through meta-learning. We show that while MAML is capable of learning such an initialization, it is restricted to a fixed number of classes while including redundancy in the learned output layer which is demonstrated to hinder learning across tasks with a high number of classes when using a low-capacity model. HIDRA solves both of these problems by training a single master neuron which is used to dynamically initialize output neurons. Experiments on common few-shot classification benchmarks demonstrate that a single HIDRA model can generalize to all number of classes independent of the number of target variables used during meta-learning. At the same time this is shown to lead to a more robust architecture which is able to train on tasks with a high number of classes, where MAML is not applicable. Finally, using a single model initialized with HIDRA is shown to improve on the results achieved with a set of models initialized with fixed output layers.
References

[1] Lukas Brinkmeyer, Rafael Rego Drumond, Randolf Scholz, Josif Grabocka, and Lars Schmidt-Thieme. Chameleon: Learning model initializations across tasks with different schemas. arXiv preprint arXiv:1909.13576, 2019.

[2] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 1126–1135. JMLR. org, 2017.

[3] Chelsea Finn, Kelvin Xu, and Sergey Levine. Probabilistic model-agnostic meta-learning. In NeurIPS, 2018.

[4] Spyros Gidaris and Nikos Komodakis. Dynamic few-shot visual learning without forgetting. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4367–4375, 2018.

[5] Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In Proceedings of the thirteenth international conference on artificial intelligence and statistics, pages 249–256, 2010.

[6] Liang-Yan Gui, Yu-Xiong Wang, Deva Ramanan, and José MF Moura. Few-shot human motion prediction via meta-learning. In Proceedings of the European Conference on Computer Vision (ECCV), pages 432–450, 2018.

[7] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In The IEEE International Conference on Computer Vision (ICCV), December 2015.

[8] Hadi Samer Jomaa, Josif Grabocka, and Lars Schmidt-Thieme. Dataset2vec: Learning dataset meta-features. ArXiv, abs/1905.11063, 2019.

[9] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

[10] Brenden Lake, Ruslan Salakhutdinov, Jason Gross, and Joshua Tenenbaum. One shot learning of simple visual concepts. In Proceedings of the annual meeting of the cognitive science society, volume 33, 2011.

[11] Yanbin Liu, Juho Lee, Mineeop Park, Saehoon Kim, Eunho Yang, Sung Ju Hwang, and Yi Yang. Learning to propagate labels: Transductive propagation network for few-shot learning. In ICLR, 2018.

[12] Alex Nichol, Joshua Achiam, and John Schulman. On first-order meta-learning algorithms. CoRR, abs/1803.02999, 2018.

[13] Boris Oreshkin, Pau Rodriguez Lpez, and Alexandre Lacoste. Tadam: Task dependent adaptive metric for improved few-shot learning. In Advances in Neural Information Processing Systems, pages 721–731, 2018.

[14] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10):1345–1359, 2010.

[15] Rajeev Ranjan, Vishal M Patel, and Rama Chellappa. Hyperface: A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(1):121–135, 2019.

[16] Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. In ICLR, 2017.

[17] Andrei A. Rusu, Dushyant Rao, Jakub Sygnowski, Oriol Vinyals, Razvan Pascanu, Simon Osindero, and Raia Hadsell. Meta-learning with latent embedding optimization. In ICLR, 2019.

[18] Nicolas Schilling, Martin Wistuba, and Lars Schmidt-Thieme. Scalable hyperparameter optimization with products of gaussian process experts. In Joint European conference on machine learning and knowledge discovery in databases, pages 33–48. Springer, 2016.

[19] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In Advances in Neural Information Processing Systems, pages 4077–4087, 2017.

[20] Flood Sung, d Li Yang, Yongxin an Zhang, Tao Xiang, Philip HS Torr, and Timothy M. Hospedales. Learning to compare: Relation network for few-shot learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1199–1208, 2018.

[21] Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip HS Torr, and Timothy M Hospedales. Learning to compare: Relation network for few-shot learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1199–1208, 2018.

[22] Oriol Vinyals, Charles Blundell, Timothy Lillicrap, Daan Wierstra, et al. Matching networks for one shot learning. In Advances in neural information processing systems, pages 3630–3638, 2016.

[23] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. Learning transferable architectures for scalable image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8697–8710, 2018.