Meta-Learning with Temporal Convolutions

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Abstract

Deep neural networks excel in regimes with large amounts of data, but tend to struggle when data is scarce or when they need to adapt quickly to changes in the task. Recent work in *meta-learning* seeks to overcome this shortcoming by training a *meta-learner* on a distribution of similar tasks; the goal is for the meta-learner to generalize to novel but related tasks by learning a high-level strategy that captures the essence of the problem it is asked to solve. However, most recent approaches to meta-learning are extensively hand-designed, either using architectures that are specialized to a particular application, or hard-coding algorithmic components that tell the meta-learner how to solve the task. We propose a class of simple and generic meta-learner architectures, based on temporal convolutions, that is domain-agnostic and has no particular strategy or algorithm encoded into it. We validate our temporal-convolution-based meta-learner (TCML) through experiments pertaining to both supervised and reinforcement learning, and demonstrate that it outperforms state-of-the-art methods that are less general and more complex.

1 Introduction

The ability to learn quickly is a key characteristic that distinguishes human intelligence from its artificial counterpart. Humans effectively utilize prior knowledge and experiences to learn new skills quickly. However, artificial learners trained with traditional supervised-learning or reinforcement-learning methods generally perform poorly when only a small amount of data is available or when they need to adapt to a changing task.

Meta-learning attempts to resolve this deficiency by broadening the learner's scope to a distribution of related tasks. Rather than training the learner on a single task, with the goal of generalizing to unseen samples from a similar data distribution, a meta-learner is trained on a distribution of similar tasks, with the goal of learning a strategy that generalizes to related but unseen tasks from a similar task distribution. A successful traditional learner discovers a rule that generalizes across data points, while a successful meta-learner devises an algorithm that generalizes across tasks. Few-shot classification is an example of a supervised setting that lends itself well to meta-learning: when there are very few labeled examples per class, a meta-learner, who learns a high-level strategy based on comparing data points, can significantly outperform a traditional learner, who learns a specific mapping from data points to classes.

Many recently-proposed methods for meta-learning have performed well at the expense of being hand-designed at either the architectural or algorithmic level. Some have been engineered with a particular application in mind, while others have aspects of a particular high-level strategy already hard-coded into them. However, the optimal strategy for an arbitrary range of tasks may not be obvious to the humans designing a meta-learner, in which case the meta-learner should have the flexibility to learn the best way to solve the tasks it is presented with. Such a meta-learner would need to have a versatile model architecture with sufficient expressive capacity in order to be able to learn a range of strategies in a variety of domains.

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Our primary contribution is a simple and generic class of model architectures for meta-learning that are based on temporal convolutions. At its core, our *temporal-convolution-based meta-learner*, or TCML, is nothing more than a deep stack of dilated convolutional layers, inspired by similar models that have been successfully used for applications ranging from image generation to text-to-speech synthesis to modeling stochastic dynamical systems [28, 27, 17]. We evaluate our TCML on few-shot image classification and multi-armed bandit problems, demonstrating both its capacity to learn a variety of algorithms on its own and its competitiveness with the state-of-the-art meta-learning approaches. It outperforms a number of approaches that are less general and/or more complex.

2 A Simple and Generic Meta-Learning Architecture

2.1 Meta-Learning Preliminaries

Before we describe our method in detail, we will introduce notation and formalize the meta-learning problem. As we briefly discussed in Section 1, the goal of meta-learning is generalization across tasks rather than across data points. Each task \mathcal{T}_i is episodic and defined by inputs x_t , outputs a_t , a loss function $\mathcal{L}_i(x_t, a_t)$, a transition distribution $P_i(x_t|x_{t-1}, a_{t-1})$, and an episode length H. A meta-learner (with parameters θ) models the distribution $\pi(a_t|x_1, \ldots, x_t; \theta)$. Given a distribution over tasks $\mathcal{T} = P(\mathcal{T}_i)$, the meta-learner's objective is to minimize its expected loss with respect to its parameters θ .

$$\min_{\theta} \mathbb{E}_{\mathcal{T}_i \sim \mathcal{T}} \left[\sum_{t=0}^{H_i} \mathcal{L}_i(x_t, a_t) \right],$$
where $x_{t+1} \sim P_i(x_t | x_{t-1}, a_{t-1}), \ a_t \sim \pi(a_t | x_1, \dots, x_t; \theta)$

A meta-learner is trained by optimizing this expected loss over tasks (or mini-batches of tasks) sampled from \mathcal{T} . During testing, the meta-learner is evaluated on unseen tasks from a different task distribution $\widetilde{\mathcal{T}}$ that is similar to the training task distribution \mathcal{T} .

In a supervised learning setting, such as regression or classification, each input x_t that the meta-learner receives is a training/test example. The corresponding output a_t is the meta-learner's prediction for the current example. The loss functions \mathcal{L}_i are regression/classification losses, such as the l_2 -loss or cross-entropy loss. The transition distributions are uniform, as supervised learning generally assumes the examples to be i.i.d.

In reinforcement learning, where the task is often defined by a Markov decsion process (MDP), the inputs x_t are the observations and rewards that the meta-learner receives from the environment, and the output a_t is a distribution over actions (which can be discrete or continuous), from which the action to take is sampled. The loss function \mathcal{L}_i is the negative of the MDP's reward function, and the transition distributions depend on the dynamics of the environment (in contrast to the supervised setting, where current outputs do not affect future inputs).

2.2 Temporal-Convolution-based Meta-Learner

Our approach is motivated by the following key principles:

- Simplicity and versatility: a meta-learner should be universally applicable to settings in both supervised and reinforcement learning. It should be generic and expressive enough to learn an optimal strategy, rather than having the strategy already built-in.
- The temporal nature of the learning process: even in a supervised classification or regression setting where the data is not sequential, meta-learning is still an inherently sequential process because the meta-learner should be able to adapt based on its successes and failures.

Santoro et al. [21] considered a similar formulation of the meta-learning problem, and explored using recurrent neural networks (RNNs) to implement a meta-learner. Their approach is simple and generic, but is significantly outperformed by methods that exploit domain or algorithmic knowledge (methods which we survey in Section 3). We hypothesize that this is because traditional RNN architectures can only propagate information forward through time via their hidden state; this temporally-linear dependency bottlenecks their capacity to perform sophistication computation on a stream of inputs. Graves et al. [8] showed that these architectures have difficulties simply storing and retrieving information, let alone performing computation with it.

van den Oord et al. [27] introduced a class of architectures that generate sequential data (in their case, audio) by performing dilated 1D-convolutions over the temporal dimension. The convolutions are causal, so that the generated values at the next timestep are only influenced by past timesteps and not future ones. Evidenced by the use of similar architectures for image generation (van den Oord et al. [28]) and modeling stochastic dynamical systems (Mishra et al. [17]), these models based on temporal convolutions (TC) are not only expressive and versatile, but lend themselves well to problems with an underlying sequential structure. Compared to traditional RNNs, the convolutional structure offers more direct, high-bandwidth access to past information, allowing them to perform more sophisticated computation on a fixed temporal segment.

However, one limitation of TC-based architectures is that, to scale to long sequences, the dilation rates generally increase exponentially, so that the the number of layers required scales logarithmically with the sequence length. This means the model has coarser access to inputs that are further back in time. To ameliorate this shortcoming, we augment the TC layers with a lightweight attention mechanism ([32]), allowing the TCML to attend over its own activations from previous timesteps. We can think of temporal convolutions as aggregating information from past timesteps, and this attention mechanism as allowing the model to pinpoint specific pieces of information. Appendix A provides a detailed description of the attention mechanism.

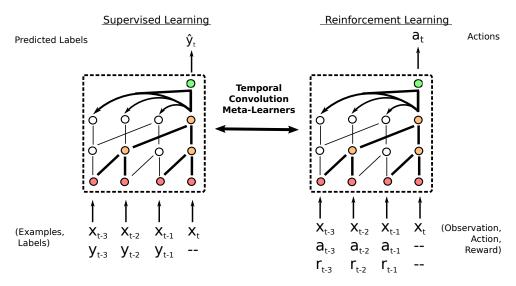


Figure 1: Overview of our temporal-convolution-based meta-learner (TCML). The same class of model architectures can be applied to both supervised and reinforcement learning.

In supervised settings, to make a prediction at timestep t, the TCML receives as input a sequence of example-label pairs $(x_1,y_1),\ldots,(x_{t-1},y_{t-1})$ for timesteps $1,\ldots,t-1$, followed by an example x_t and zeros. Its output at time t is its prediction for x_t . In reinforcement-learning settings, it receives a sequence of state-action-reward tuples $(x_1,a_1,r_1),\ldots,(x_{t-1},a_{t-1},r_{t-1})$, followed x_t and zeros. Its output at time t is a distribution over actions a_t . If any of the inputs are images, we employ an additional stack of spatial convolutions (an embedding network that is also learned) that converts the image into a feature vector before it is passed into the TCML.

Many techniques have been proposed to increase the capacity or accelerate the training of deep convolutional architectures, including batch normalization (Ioffe and Szegedy [12]), residual connections (He et al. [9]), and dense connections (Huang et al. [11]). We found that these techniques greatly improved the expressive capacity and training speed of TCMLs, and also that no particular choice of residual/dense configurations was essential for good performance.

3 Related Work

Pioneered by Thrun and Pratt [26], Schmidhuber [22], Naik and Mammone [19], meta-learning is not a new idea. A key tradeoff central to many recent meta-learning approaches is between performance and generality; we will discuss several notable methods and how they fit into this paradigm.

Several approaches for few-shot classification have demonstrated good performance with specialized neural network architectures. Koch [14] used a Siamese network that was trained to predict whether

two images belong to the same class. Vinyals et al. [30] learned an embedding function and used cosine distance in an attention kernel to judge image similarity. Snell et al. [25] employed a similar approach to Vinyals et al. [30], but used Euclidean distance with their embedding function. All three methods work well within the context of classification, but are not readily applicable to other domains, because a strategy based on comparing data points is built into them.

A number of methods consider a meta-learner that makes updates to the parameters of a traditional learner [10, 4]. Both Andrychowicz et al. [1] and Li and Malik [16] investigated the setting of learning to optimize, where the learner is an objective function to minimize, and the meta-learner uses the gradients of the learner to perform the optimization. Their meta-learner was implemented by an LSTM and the strategy that it learned can be interpreted as a gradient-based optimization algorithm.

Ravi and Larochelle [20] extended this idea, using a similar LSTM meta-learner in a few-shot classification setting, where the traditional learner was a convolutional-network-based classifier. In this setting, the whole meta-learning algorithm is decomposed into two parts: the traditional learner's initial parameters are trained to be suitable for fast gradient-based adaptation; the LSTM meta-learner is trained to be an optimization algorithm adapted for meta-learning tasks. Finn et al. [6] explored a special case where the meta-learner is constrained to use ordinary gradient descent to update the learner and showed that this simplified model can achieve very competitive performance. Munkhdalai and Yu [18] explored a more sophisticated weight update scheme that improved performance.

All of the methods discussed in the previous paragraph have the benefit of being domain independent, but they explicitly encode a particular strategy for the meta-learner to follow (namely, adaptation via gradient descent at test time). On a particular domain, there may exist better strategies, but these methods will be unable to discover them. In contrast, TCML presents a alternative paradigm where an expressive but generic architecture has the capacity to learn different algorithms on its own.

Graves et al. [8] investigated the use of recurrent neural networks (RNNs) to solve algorithmic tasks. They experimented with a meta-learner implemented by an LSTM, but their results suggested that LSTM architectures are ill-equipped for these kinds of tasks. They then designed a more sophisticated RNN architecture, where a feedforward or LSTM controller was coupled to an external memory bank from which it can read and write, and demonstrated that these memory-augmented neural networks (MANNs) achieved substantially better performance than LSTMs. Santoro et al. [21] evaluated both LSTM and MANN meta-learners on few-shot image classification, and confirm the inadequacy of the LSTM architecture. These approaches are generic, but MANNs feature a complicated memory-addressing architecture that is difficult to train.

Out of all the prior methods we've discussed, TCML is closest in spirit to Santoro et al. [21]; however, our experiments indicate that TCML outperforms such traditional RNN architectures. We can view the TCML architecture as a flavor of RNN that can remember information through the activations of the network rather than through an explicit memory module. Because of its convolutional structure, the TCML better preserves the temporal structure of the inputs it receives, at the expense of only being able to remember information for a fixed amount of time. However, by exponentially increasing the dilation factors of the higher convolutional layers (as done by van den Oord et al. [27]), TCML architectures can tractably store information for long periods of time.

A challenge unique to meta-learning in reinforcement learning (RL) settings is the exploration-exploitation tradeoff. A RL agent must explore an environment, gathering information about what the task is and what behaviors are possible, and then eventually exploit its knowledge for maximum rewards, once confident that it has explored sufficiently. Duan et al. [5] and Wang et al. [31] both investigated meta-RL and demonstrated that their meta-learners could explore and exploit in the context of multi-arm bandit problems and finite MDPs. They both used traditional RNN architectures (GRUs and LSTMs) to implemented their meta-learners. In both of these works, the bottleneck to scaling up meta-RL appears to be the availability of numerous complex and diverse environments for training, rather than the capacity of the model used.

If the task distribution used in training is not complex enough, the resulting meta-RL-learner may simply learn an optimal policy for each environment, and then learn to detect which previously-seen environment it is in, limiting the range of environments that it generalizes to. Finn et al. [6] experimented with fast adaptation of policies for reinforcement learning, where the meta-learner was trained on a distribution of closely-related locomotion tasks. It successfully learned to adapt its gait according to current environment by learning how to perform system identification.

4 Experiments

Our experiments were designed to investigate the following questions:

- How does TCML's generality affect its performance on a range of meta-learning tasks?
- How does its performance compare to existing approaches that are specialized to a particular task domain, or have elements of high-level strategy already built-in?

4.1 Few-Shot Image Classification

In the few-shot classification setting, we wish to classify data points into N classes, when we only have a small number (K) of labeled examples per class. A meta-learner is readily applicable, because it learns how to compare input points, rather than memorize a specific mapping from points to classes. Figure 2 illustrates how few-shot image classification fits into the meta-learning formalization presented in Section 2.1 and our introduction of the TCML in Section 2.2.

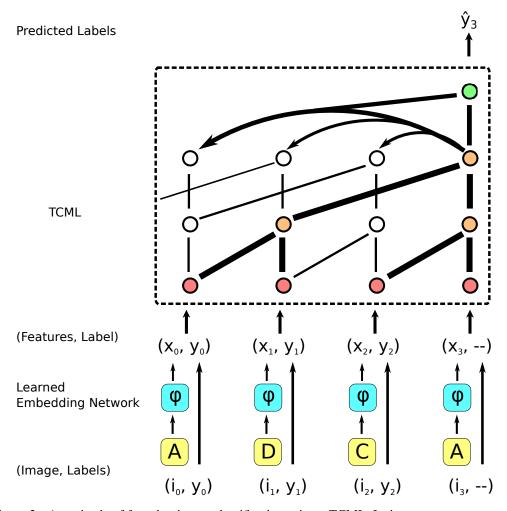


Figure 2: An episode of few-shot image classification using a TCML. Its inputs are a sequence of feature vectors x_1,\ldots,x_t (produced by an embedding network ϕ from images i_1,\ldots,i_t) and their labels y_1,\ldots,y_{t-1} . Qualitatively, to make the correct prediction at time t=3, the TCML would need to (i) determine that x_3,x_0 look more similar than x_3,x_1 or than x_3,x_2 , and then (ii) remember that the label for x_0 was y_0 , and (iii) accordingly output y_0 as its prediction for \hat{y}_3 . Thus, for the TCML to succeed at few-shot image classification, it needs to learn how to compare images and evaluate their similarity, but nowhere is such a comparison-based strategy built into the model.

Omniglot and mini-Imagenet are two datasets for few-shot image classification. Introduced by Lake et al. [15], Omniglot consists of black-and-white images of handwritten characters gathered from 50 languages, for a total of 1632 different classes with 20 instances per class. Like prior works, we downsampled the images to 28×28 and randomly selected 1200 classes for training and 432 for testing. We performed the same data augmentation proposed by Santoro et al. [21], forming new classes by rotating each member of an existing class by a multiple of 90 degrees. Mini-ImageNet is a more difficult benchmark, consisting of 84×84 color images from 100 different classes with 600 instances per class. It comprises a subset of the well-known ImageNet dataset, providing the complexity of ImageNet images without the need for substantial computational resources. We used the split released by Ravi and Larochelle [20] with 64 classes for training, 16 for validation, and 20 for testing.

To evaluate a TCML on the N-way, K-shot problem, we sample N classes and K examples of each class, and fed the corresponding NK example-label pairs to the model in a random order, followed by a new, unlabled example from one of the N classes. We report the average accuracy on this last, (NK+1)-th timestep.

We tested the TCML on 5-way Omniglot, 20-way Omniglot, and 5-way mini-Imagenet. For each of these three splits, we trained the TCML on episodes where the number of shots K was chosen uniformly at random from 1 to 5. (note that this is unlike prior works, who train separate models for each shot). For a K-shot episode within an N-way problem, the loss was simply the average cross-entropy between the predicted and true label on the (NK+1)-th timestep. For a complete description of our TCML architecture, we refer the reader to Appendix B.

Table 1 displays our results on 5-way and 20-way Omniglot, and Table 2 has the results for 5-way mini-Imagenet. We see that the TCML outperforms state-of-the-art methods that are extensively hand-designed, and/or domain-specific. It significantly exceeds the performance of methods such as Santoro et al. [21] that are similarly simple and generic.

Table 1: 5-way and 20-way, 1-shot and 5-shot classification accuracies on Omniglot, with 95% confidence intervals where reported. For each task, the best-performing method is highlighted, along with any others whose confidence intervals overlap.

Method	5-Way Omniglot		20-Way Omniglot	
	1-shot	5-shot	1-shot	5-shot
Santoro et al. [21]	82.8%	94.9%	_	_
Koch [14]	97.3%	98.4	88.2%	97.0%
Vinyals et al. [30]	98.1%	98.9%	93.8%	98.5%
Finn et al. [6]	$\textbf{98.7\%} \pm \textbf{0.4\%}$	$\textbf{99.9\%} \pm \textbf{0.3\%}$	$95.8\% \pm 0.3\%$	98.9% 0.2%
Snell et al. [25]	97.4%	99.3%	96.0%	98.9%
Munkhdalai and Yu [18]	98.9%	_	97.0%	_
TCML, Ours	$98.96\% \pm 0.20\%$	99.75% \pm 0.11%	97.64% ± 0.30%	99.36% ± 0.18%

Table 2: 5-way, 1-shot and 5-shot classification accuracies on Omniglot and mini-Imagenet, with 95% confidence intervals where reported. For each task, the best-performing method is highlighted, along with any others whose confidence intervals overlap.

Method	5-Way Mini-ImageNet			
	1-shot	5-shot		
Vinyals et al. [30]	43.6%	55.3%		
Finn et al. [6]	$48.7\% \pm 1.84\%$	$63.1\% \pm 0.92\%$		
Ravi and Larochelle [20]	$43.4\% \pm 0.77\%$	$60.2\% \pm 0.71\%$		
Snell et al. [25]	$46.61\% \pm 0.78\%$	$65.77\% \pm 0.70\%$		
Munkhdalai and Yu [18]	$49.21\% \pm 0.96\%$	_		
TCML, Ours	55.71% ± 0.99%	$68.88\% \pm 0.92\%$		

For Omniglot, our embedding network used a similar architecture to the one proposed in Vinyals et al. [30], consisting of 4 blocks of $\{3 \times 3 \text{ conv } (64 \text{ filters}), \text{ batch normalization, leaky ReLU activation } (leak 0.1), and <math display="inline">2 \times 2 \text{ max-pooling} \}$. The output was then flattened and passed through a fully-connected layer to get a 64-dimensional feature vector.

For mini-ImageNet, our embedding network took inspiration from architectures commonly used for the full ImageNet dataset by He et al. [9] and Simonyan and Zisserman [24], as we found that the shallower architectures used by previous works did not make full use of the TCML's expressive capacity. Our model architecture is described in detail in Appendix C.

In all cases, the TCML and embedding were trained end-to-end and jointly ¹ using Adam [13].

In addition to comparisons with prior work, we also considered a number of ablations:

- Using nearest-neighbors on the features learned by the Omniglot embedding. With Euclidean distances, this achieves 65.1% and 67.1% on 1-shot and 5-shot, respectively. With cosine distances, it achieves 67.7% and 68.3%. This indicates that the TCML learned a more sophisticated strategy for performing comparisons than a traditional distance metric.
- Replacing the TCML with a stacked LSTM. We experimented with a similar number
 of parameters to the TCML, varying the number of layers and their sizes. The best
 model achieved 78.1% on 1-shot Omniglot and 90.8% on 5-shot, demonstrating the low
 information-bandwidth capacity of traditional RNN architectures.
- Using the method of Finn et al. [6] (which relies on the built-in strategy of adaptation via gradient descent at test time) using our mini-Imagenet embedding architecture. They ran the experiment for us using the original implementation of their method. The performance was substantially worse than the numbers they reported using the shallower embedding (30% on 1-shot mini-Imagenet), indicating that the TCML's performance cannot be solely attributed to the deeper embedding.
- Using the attention mechanism without the TC layers. This is related to the method of Vinyals et al. [30]; they modify the feature vectors before applying attention using an LSTM, and explicitly use the attention operation to form their prediction as a linear combination of the known labels. Accordingly, we found that this baseline's performance was slightly worse than the reported performance of Vinyals et al. [30].

4.2 Multi-Armed Bandits

In the supervised classification setting, a successful meta-learner must learn a strategy that involves making comparisons between different examples. To explore whether our TCML can learn different types of algorithms, such as those related to reinforcement learning, we explore its performance on the multi-armed bandit problem, which can be summarized as follows: at each timestep, an agent selects one of K arms, and receives a reward according to some unknown distribution. The agent's goal is to maximize its total reward over an episode of duration N. To perform well in this setting, a meta-learner must learn to balance both exploration and exploitation. It must begin by selecting different arms to find the ones with favorable reward distributions (exploring), and decide when to transition into repeatedly selecting the best ones (exploiting its knowledge for maximum rewards).

This exploration-exploitation tradeoff is one of the core algorithmic nuances that distinguishes reinforcement learning from supervised learning, and so a meta-learner capable of learning RL algorithms must learn to address it. The multi-armed bandits problem captures this tradeoff and is well-studied, making it a suitable candidate to explore how TCMLs fare in an exploration-exploitation setting. There also exist several hand-designed algorithms [7, 3, 2] with optimality guarantees that can serve as baselines.

Duan et al. [5] and Wang et al. [31] both explored using meta-learners implemented by RNNs in bandit problems; the former released more substantial details about their experimental setup, and so we designed our experiments to be directly comparable to theirs.

Within every episode, each bandit's rewards are drawn from a Bernoulli distribution, with parameter p chosen uniformly at random between 0 and 1. At each timestep, the meta-learner receives a length

¹In previous versions of this paper, we pretrained the embedding for the mini-ImageNet model, and retrained the model on the training and validation sets after using the latter for hyperparameter selection. In this version, we did neither in order to make our results more comparable to prior work.

K one-hot vector indicating the arm selected at the previous timestep, and the corresponding reward. It outputs a discrete probability distribution over the K arms; the arm to select is determined by sampling from this distribution.

We compared our TCML to the GRU architecture used by Duan et al. [5], and several baselines with varying optimality guarantees. The Gittins index [7] is the Bayes optimal solution in the discounted, infinite-horizon setting, and serves as an oracle against which to benchmark performance. We trained our TCML with trust region policy optimization (Schulman et al. [23]) using the same hyperparameters as Duan et al. [5], and tested all combinations of N=10,100,500 and K=5,10,50. To test the scalability of our TCML as compared to traditional RNN architectures, we also tested N=1000, K=50. For a detailed description of the other baselines and other experimental details, we refer the reader to Duan et al. [5]'s paper. Appendix D describes our TCML architecture.

The results are summarized in Table 4.2. For all baseline methods, we report the values from Duan et al. [5] (the last row is the only exception, since they did not test that scenario). The values reported are the average reward per episode of length N, averaged over 1000 episodes, with 95% confidence intervals. We observe that the gap between the Gittins index (oracle) and the meta-learners grows with the size of the problem. However, there is a significant gap between TCML and Duan et al. [5] in the N=1000, K=50 setting, which suggests that the GRU architecture they used is nearing its capacity. Figure 3 displays a learning curve for this scenario, where the difference is quite pronounced; the TCML learns both faster and better than the GRU.

Environment	Method					
	Random	ϵ -greedy	UCB-1	Gittins	Duan et al. [5]	Ours
N = 10, K = 5	5.0	6.6	6.7	6.6	6.7	6.68 ± 0.14
N = 10, K = 10	5.0	6.6	6.7	6.6	6.7	$\textbf{6.73} \pm \textbf{0.13}$
N = 10, K = 50	5.1	6.5	6.6	6.5	6.8	$\textbf{6.72} \pm \textbf{0.14}$
N = 100, K = 5	49.9	75.4	78.0	78.3	78.7	79.11 ± 1.04
N = 100, K = 10	49.9	77.4	82.4	82.8	83.5	$\textbf{83.46} \pm \textbf{0.80}$
N = 100, K = 50	49.8	78.3	84.3	85.2	84.9	$\textbf{85.15} \pm \textbf{0.64}$
N = 500, K = 5	249.8	388.2	405.8	405.8	401.5	408.09 ± 4.92
N = 500, K = 10	249.0	408.0	438.9	437.8	432.5	432.42 ± 3.45
N = 500, K = 50	249.6	413.6	457.6	463.7	438.9	442.58 ± 2.49
N = 1000, K = 50	499.8	845.2	926.3	944.1	847.43 ± 6.86	889.79 ± 5.63

Table 3: Performance on a range of multi-arm bandit problems. For each, we highlighted the best performing method, and any others whose performance is not statistically significantly different.

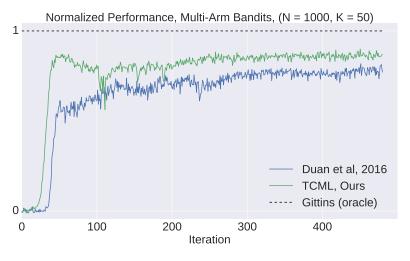


Figure 3: Learning curve for multi-arm bandits, N=1000, K=50. The vertical axis is normalized such that a random policy scores 0, and the Gittins index scores 1.

5 Conclusion and Future Work

We presented a simple and generic class of model architectures for meta-learning. By evaluating them on few-shot image classification and multi-arm bandit problems, we demonstrated that these temporal-convolution-based meta-learners, or TCMLs, are versatile enough to perform well in variety of domains and can surpass the performance of methods that are substantially more hand-engineered or are tailored to a particular domain.

Meta-learning holds enormous potential as an avenue towards artificial agents learning general-purpose algorithms and reusing prior knowledge for efficient learning of new skills. TCMLs have shown themselves to be an encouraging meta-learning technique, despite their simplicity and generality. Directions for future work include exploring their performance in more complex domains, and we hope that they inspire many advances in meta-learning.

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Appendix

A TCML Attention Mechanism

We styled our attention mechanism based on the recent work of Vaswani et al. [29]. Let $\{s_1,\ldots,s_t\}$ denote the activations at each timestep (where each $s_i \in \mathbb{R}^d$) for some layer in the TCML at which we wish to incorporate attention. The key matrix K has shape $d \times (t-1)$ and is formed by concatenating $\{s_1,\ldots,s_{t-1}\}$; the values matrix K has shape K has shape K has shape K has shape K and is formed by applying a K d' linear layer to K. The query vector K is constructed by passing K through a small feed-forward network. The output of this causal attention operation is then given by:

$$\operatorname{softmax}(\frac{q^TK}{\sqrt{d}})V^T$$

In our experiments, we found that setting $q=s_t$ worked just as well as passing it through a feed-forward network; therefore, we report results using the former scheme. We used this attention mechanism after the final convolutional layers (although it could conceivably be used elsewhere and/or at multiple layers in the network) and set d'=16 and d'=48 for 5-way and 20-way tasks respectively.

B TCML Architecture for Few-Shot Image Classification

Here we describe the TCML model architecture used for the experiments involving few-shot image classification. We used both residual [9] and dense [11] connections in our model, as both have been shown to improve both the expressiveness and training speed of deep convolutional networks. In particular, we used a nested structure where inner blocks used residual connections and outer blocks used dense connections.

Figure 4 depicts residual and dense blocks, along with the entire TCML architecture we used. The Omniglot model had about 5 million parameters, and the mini-Imagenet model had about 11 million.

All causal convolutions had kernel size 2, and we used the following activation function (as introduced by van den Oord et al. [28, 27]):

$$\tanh(W_f * s) \odot \sigma(W_q * s)$$

where * denotes convolution, $\sigma(\cdot)$ is the sigmoid function, \odot denotes elementwise-multiplication, s is the input to the layer, and W_f, W_g are network weights to be learnt.

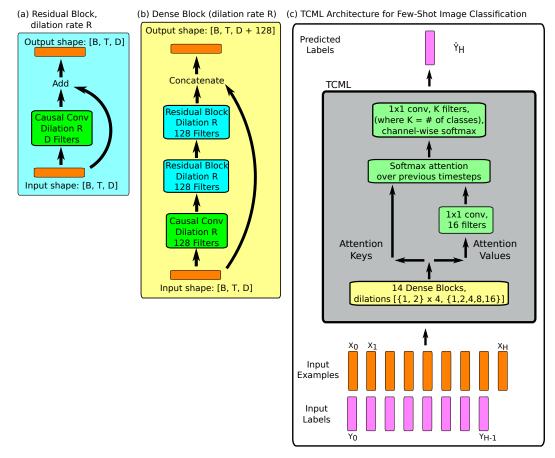


Figure 4: The TCML architecture we used for few-shot image classification. Where input and output shapes are indicated, the dimensions are (batch size, B) × (sequence length, T) × (number of channels, D). From left to right: (a) A residual block performs a causal convolution and adds the output to the input. (b) The dense blocks in our model utilize a series of causal convolutions and residual blocks like in (a), and then concatenate the output to the inputs. (c) The full model primarily consists of a series of dense blocks. We used the same TCML architecture for both datasets. For 20-way OmniGlot we added 2 extra dense blocks at the end with dilation 32 and 64 to account for the increased sequence length.

C Embedding Network Architecture for mini-Imagenet

Our embedding network for mini-Imagenet also used residual connections. We used residual blocks that contained a series of convolution layers, followed by a residual connection and then a 2×2 max-pooling operation. The structure of the residual blocks, as well as the entire network architecture, is illustrated in Figure 5. We used dropout of 0.5 in the later layers (indicated in the figure) to help prevent overfitting.

(a) Residual Block, D filters (b) mini-Imagenet embedding 512-dimensional feature vector 2x2 max-pool dropout 0.5, 1x1 conv, 512 filters Add batch norm dropout 0.5, 3x3 conv, D filters 1x1 conv, 2048 filters, batch norm 6x6 mean pool, ReLU leaky ReLU (leak 0.1) Residual Block, 256 filters 3x3 conv, D filters 1x1 conv, batch norm D filters leaky ReLU (leak 0.1) Residual Block, 128 filters 3x3 conv, D filters batch norm leaky ReLU (leak 0.1) Residual Block, 96 filters Residual Block, 64 filters 84x84x3 image

Figure 5: Left (a), the residual blocks used in our mini-Imagenet embedding, and right (b) the entire network architecture, which had 14 layers and about 3 million parameters. Its input is an 84×84 color image and it outputs a 512-dimensional feature vector.

D TCML Architecture for Multi-Armed Bandits

The TCML architecture we used for multi-armed bandit experiments was a smaller but closely-related version of the one illustrated in Figure 4.

For the bandit problem with N timesteps and K arms, we chose the number of layers to be $\min x: 2^x \geq N$, to ensure that the network's receptive field was at least as long as the length of the episode. We did not use residual connections or attention, but used dense connections between every causal layer. All causal convolutions had 64 channels, and the dilation factor doubled at each layer. We used a 1×1 convolution with 128 filters before the first causal layer, and a 1×1 convolution with K filters after the last causal layer (the latter outputs the log-probability of choosing each of the K arms).