Multi-Modal Fusion by Meta-Initialization

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Abstract

When experience is scarce, models may have insufficient information to adapt to a new task. In this case, auxiliary information—such as a textual description of the task—can enable improved task inference and adaptation. In this work, we propose an extension to the Model-Agnostic Meta-Learning algorithm (MAML), which allows the model to adapt using auxiliary information as well as task experience. Our method, Fusion by Meta-Initialization (FuMI), conditions the model initialization on auxiliary information using a hypernetwork, rather than learning a single, task-agnostic initialization. Furthermore, motivated by the shortcomings of existing multi-modal few-shot learning benchmarks, we constructed iNat-Anim—a large-scale image classification dataset with succinct and visually pertinent textual class descriptions. On iNat-Anim, FuMI significantly outperforms uni-modal baselines such as MAML in the few-shot regime. The code for this project and a dataset exploration tool for iNat-Anim are publicly available at https://github.com/s-a-malik/multi-few.

1 Introduction

Learning effectively in resource-constrained environments is an open challenge in machine learning [1,2,3]. Yet humans are capable of rapidly learning new tasks from limited experience, in part by drawing on auxiliary information about the task. This information can be particularly helpful in the few-shot regime, as it can highlight features that have not been seen directly in task experience, but are necessary to solve the task. For example, Figure 1 shows an example image classification task where a text description of the class contains discriminative information that is not contained in the training (support) images. Designing algorithms that can incorporate auxiliary information into meta-learning approaches has consequently attracted much attention [4,5,6,7,8,9,10].

Model-agnostic meta-learning (MAML) [1] is a popular method for few-shot learning. However, it cannot incorporate auxiliary task information. In this work, we propose Fusion by Meta-Initialization (FuMI), an extension of MAML which uses a hypernetwork [11] to learn a mapping from auxiliary task information to a parameter initialization. While MAML learns an initialization that facilitates rapid learning across all tasks, FuMI conditions the initialization on the specific task to enable improved adaption.

Existing multi-modal few-shot learning benchmarks largely rely on hand-crafted feature vectors for each class [12,13], or use noisy language descriptions from sources such as Wikipedia [14,15].

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Figure 1: An example few-shot learning task, using images and class descriptions from our proposed dataset, iNat-Anim. Here, we see the class description contains information (the colour of the bird’s breast) which is not found in the class images (as they are all turned away).

For this reason, we release iNat-Anim—a large animal species image classification dataset with high quality descriptions of visual features. On this benchmark, we find that FuMI significantly outperforms MAML in the very-few-shot regime.

2 Background

In the meta-learning framework [1], we suppose tasks are drawn from a task distribution \( p(T) \). At meta-train time, the model \( f_\theta \) is evaluated on a series of tasks \( T_i \in D_{\text{train}} \), where \( D_{\text{train}} \) is a finite set of samples from \( p(T) \). This gives task loss \( L_{T_i} \), which is used to update the model parameters \( \theta \) in accordance with the meta-learning algorithm. At meta-test time, the trained model is evaluated on all tasks in \( D_{\text{test}} \), another set of samples from \( p(T) \).

In an \( N \)-shot, \( K \)-way multi-modal classification problem\(^2\), a task \( T = (S, Q) \) is defined by a support set \( S = \{(x_{i,j}, y_i, t_i)\}_{i=1}^{K} \) and a query set \( Q = \{(x_{i,j}, y_i)\}_{i=1}^{K} \), where \( M \) is the number of query shots. The support set contains \( N \) samples and auxiliary class information \( t_i \) for each of the \( K \) classes, which are used by the meta-learner to train an adapted model. Once this has been trained, the adapted model is evaluated on the unseen query set, giving task loss \( L_Q \). In the context of our work, \( t_i \) denotes the textual description of the class \( y_i \), meaning each class has a textual description and \( N \) support images. Figure 1 shows an example task using the notation outlined here.

3 Data

Existing Multi-Modal Few-shot Benchmarks. While there are a number of popular uni-modal few-shot learning benchmarks [16, 17, 18], multi-modal benchmarks are less common. Some works simply extend few-shot benchmarks by using the class label as auxiliary information [6, 19]. Benchmarks explicitly incorporating auxiliary modalities include Animals with Attributes (AWA) [12] and Caltech-UCSD-Birds (CUB) [13] which augment images of animals/birds with hand-crafted class attributes. While semantic class features can be highly discriminative, they require manual labelling and are thus difficult to obtain at scale. Recent work instead uses the more general approach of using natural language descriptions, for example, through augmenting CUB with Wikipedia articles [14, 15]. However, these articles are subject to change and visual information is sparse, thus reducing the relative benefit of the auxiliary information.

The iNat-Anim Dataset. Motivated by these shortcomings, we constructed the iNat-Anim\(^3\) dataset. iNat-Anim consists of 195,605 images across 673 animal species, which is orders of magnitude larger than existing benchmarks (AWA and CUB). The images are a subset of the iNaturalist 2021 CVPR challenge [20] and have been augmented with textual descriptions from Animalia [21] to provide

\(^2\)For consistency with our dataset, the problem setting formulation is for classification. However our method can also be applied to regression and reinforcement learning.

\(^3\)https://doi.org/10.5281/zenodo.6703088
auxiliary information about each species. The descriptions are typically short and are qualitatively pertinent to the visual characteristics of the animal (Figure 1). See Appendix C for further details.

4 Method

We propose Fusion by Meta-Initialization (FuMI): a gradient-based model for multi-modal few-shot learning. This model extends MAML by conditioning the meta-initialization of task-specific model parameters on their associated task information, thereby incorporating the auxiliary information into the tuned model.

Suppose we are training a neural network for \( K \)-way classification, with a fully-connected final layer (head). The parameters of the final layer \( \theta_{\text{Head}} \) can be partitioned such that each \( \theta_{\text{Head}}^i \) generates the class probability density \( p(c_i|x) \) for a particular class \( c_i \). MAML learns an initialization \( \theta = (\theta_{\text{Head}}, \theta_{\text{Body}}) \) and updates it with gradient descent in the inner-loop, uninformed by the auxiliary task information \( t \). However, given \( t \), we may instead condition the initialization of each class head \( \theta_{\text{Head}}^i \) on the auxiliary information for its associated class \( t_i \), thereby generating a class-specific initialization.

In FuMI (Algorithm 1), we use a hypernetwork \( g_{\phi} \) to generate this initialization for the final layer, by computing \( \theta_{\text{Head}}^i = g_{\phi}(t_i) \) for each class description \( t_i \). As in MAML, a shared initialization \( \theta_{\text{Body}} \) is used for the remainder of the network. All network weights \( \theta \) are then tuned by gradient descent in the inner loop, giving \( \theta' \). In the outer loop, the query set loss \( L_{Q}(f_{\theta'}) \) is used to update both the network body initialization \( \theta_{\text{Body}} \) and hypernetwork parameters \( \phi \).

Algorithm 1 FuMI for few-shot classification, with differences from MAML in red.

```plaintext
Require: \( p(T) \): distribution over tasks
Require: \( \alpha, \beta \): step size hyperparameters
Randomly initialize \( \theta_{\text{Body}}, \phi \)
while not done do
  Sample task \((S, Q) \sim p(T)\)
  for all class information \( t_i \) in \( S \) do
    \( \theta_{\text{Head}}^i = g_{\phi}(t_i) \)
  end for
  \( \theta = (\theta_{\text{Head}}, \theta_{\text{Body}}) \)
  Adapt parameters \( \theta' = \theta - \alpha \nabla_\theta L_{S}(f_{\theta}) \)
  Update network body initialization \( \theta_{\text{Body}} \leftarrow \theta_{\text{Body}} - \beta \nabla_{\theta_{\text{Body}}} L_{Q}(f_{\theta'}) \)
  Update hypernetwork \( \phi \leftarrow \phi - \beta \nabla_{\phi} L_{Q}(f_{\theta'}) \)
end while
```

5 Experiments

5.1 Setup

Experimental set-up The multi-modal few-shot problem is described in Section 2. We evaluated 5-way classification accuracy on iNat-Anim with up to 10 shots. We report the average meta-test accuracy for each model across 5 random seeds. The meta-test split consisted of 1,000 randomly sampled tasks where all classes in this split had not previously been seen in training. Each test task had 20 randomly-sampled query images from each class, ensuring there was no dataset imbalance.

Baselines We compared few-shot learning performance of FuMI to MAML as a natural uni-modal baseline. We additionally compare performance to metric-based meta-learning approaches: 1) Prototypical Networks [2], which computes a mean image embedding (prototype) for each class and classifies query images as the class corresponding to the closest prototype by Euclidean distance, 2) AM3 [3], a multi-modal extension to Prototypical Networks, which learns an adaptable convex combination of the image prototype with another prototype computed from the auxiliary modality.

We used the same pre-trained image and text encoders (BERT [22] and ResNet-152 [23]) for all models to enable fair comparison across methods. Appendix B discusses implementation details.

5.2 Results

Multi-modal fusion improves performance in the very-few-shot regime. Figure 2 shows the relative performance gain of FuMI compared to MAML. We find that using the task-specific initialization provides significant improvements given very limited task data, whilst performance is similar with additional examples. This is as expected, since the relative information gain from auxiliary information is greater when there are fewer examples per class.
Table 1: Few-shot classification accuracy for uni-modal (top) and multi-modal (bottom) models on iNat-Anim over 5 random seeds.

| Model          | 0-shot | 1-shot | 3-shot | 5-shot | 10-shot |
|----------------|--------|--------|--------|--------|---------|
| Proto. Nets [2] | 71.7(2)| 83.9(3)| 85.9(2)| 88.3(2)|         |
| MAML [1]       | 72(1)  | 81(1)  | 84(2)  | 87.1(1)|         |
| AM3 [6]        | 71.0(8)| 80.8(4)| 85.9(5)| 86.3(6)| 88.5(2) |
| FuMI (ours)    | 78.9(4)| 82.7(6)| 85.1(4)| 87.1(2)|         |

Metric-based methods outperform gradient-based methods on iNat-Anim. Table 1 shows the results for FuMI against the other uni- and multi-modal baselines. We find that FuMI under-performs compared to the other meta-learning approaches. We note that gradient-based meta-learning models can be particularly sensitive to hyperparameters. Metric-based approaches were observed to be more robust on our dataset.

6 Related Work

A range of other MAML extensions have been recently proposed, with improvements including training stability [24], avoiding computational overhead from second-order derivatives [25, 26], and exploration in meta-reinforcement learning [27]. Vuorio et al. [28] use the entire uni-modal support set (rather than auxiliary task information) to modulate the initialization of the entire network. Raghu et al. [29] find no decrease in performance when updating only the network head in the inner loop, thereby concluding that the features learned in the network body are directly reused across tasks. Based on this, in addition to early experimentation, we use the hypernetwork to directly initialize only the network head in FuMI. An alternative approach to few-shot learning is metric-based meta-learning [2, 6, 30, 31], which we evaluate on iNat-Anim in Section 5.

7 Conclusions

Contributions In this work, we have introduced Fusion by Meta-Initialization, a multi-modal gradient-based meta-learning algorithm. FuMI significantly outperforms MAML baselines given very limited data, highlighting the effectiveness of auxiliary information on few-shot performance. To fill the need for large-scale benchmarks, we also constructed iNat-Anim, a few-shot image classification dataset with high-quality class descriptions. We hope that this will enable further work on the intersection of meta-learning and multi-modal models.

Limitations and Further Work Methodologically, we note that the gradient-based inner-loop of FuMI makes it vulnerable to catastrophic forgetting of the auxiliary information used for initialization. Insights from continual learning could help mitigate against this [32]. Experimentally, we plan to broaden our evaluation of FuMI to further image-text few-shot benchmarks [13]. In addition, it would be informative to evaluate on other modalities (e.g. audio [33]) as well as multi-modal regression and reinforcement learning tasks.
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References

[1] Chelsea Finn, Pieter Abbeel, and Sergey Levine. “Model-agnostic meta-learning for fast adaptation of deep networks”. In: International conference on machine learning. PMLR. 2017, pp. 1126–1135.

[2] Jake Snell, Kevin Swersky, and Richard Zemel. “Prototypical networks for few-shot learning”. In: Advances in neural information processing systems 30 (2017).

[3] Yaqing Wang et al. “Generalizing from a few examples: A survey on few-shot learning”. In: ACM computing surveys (csur) 53.3 (2020), pp. 1–34.

[4] Yao Ma et al. “Multimodality in meta-learning: A comprehensive survey”. In: Knowledge-Based Systems (2022), p. 108976.

[5] Mengmeng Ma et al. “SMIL: Multimodal learning with severely missing modality”. In: Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 35. 3. 2021, pp. 2302–2310.

[6] Chen Xing et al. “Adaptive cross-modal few-shot learning”. In: Advances in Neural Information Processing Systems 32 (2019).

[7] Zeynep Akata et al. “Label-embedding for image classification”. In: IEEE transactions on pattern analysis and machine intelligence 38.7 (2015), pp. 1425–1438.

[8] Xin Wang et al. “Tafe-net: Task-aware feature embeddings for low shot learning”. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019, pp. 1831–1840.

[9] Yao-Hung Hubert Tsai, Liang-Kang Huang, and Ruslan Salakhutdinov. “Learning robust visual-semantic embeddings”. In: Proceedings of the IEEE International conference on Computer Vision. 2017, pp. 3571–3580.

[10] Edgar Schonfeld et al. “Generalized zero-and few-shot learning via aligned variational autoencoders”. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019, pp. 8247–8255.

[11] David Ha, Andrew Dai, and Quoc V Le. “Hypernetworks”. In: arXiv preprint arXiv:1609.09106 (2016).

[12] Yongqin Xian et al. “Zero-Shot Learning—A Comprehensive Evaluation of the Good, the Bad and the Ugly”. In: IEEE Transactions on Pattern Analysis and Machine Intelligence 41.9 (2019), pp. 2251–2265. DOI: [10.1109/TPAMI.2018.2857768]

[13] Catherine Wah et al. “The caltech-ucsd birds-200-2011 dataset”. In: (2011).

[14] Tzuf Paz-Argaman et al. “ZEST: Zero-shot learning from text descriptions using textual similarity and visual summarization”. In: arXiv preprint arXiv:2010.03276 (2020).

[15] Mohamed Elhoseiny et al. “Link the head to the” beak”: Zero shot learning from noisy text description at part precision”. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2017, pp. 5640–5649.

[16] Oriol Vinyals et al. “Matching networks for one shot learning”. In: Advances in neural information processing systems 29 (2016).

[17] Brenden M Lake, Ruslan Salakhutdinov, and Joshua B Tenenbaum. “Human-level concept learning through probabilistic program induction”. In: Science 350.6266 (2015), pp. 1332–1338.

[18] Grant Van Horn et al. “The inaturalist species classification and detection dataset”. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2018, pp. 8769–8778.

[19] Eli Schwartz et al. “Baby steps towards few-shot learning with multiple semantics”. In: Pattern Recognition Letters 160 (2022), pp. 142–147.
Grant Van Horn and Oisin Mac Aodha. iNat Challenge 2021. URL: https://sites.google.com/view/fgvc8/competitions/inatchallenge2021?authuser=0

Online animals encyclopedia. https://animalia.bio/

Jacob Devlin et al. “Bert: Pre-training of deep bidirectional transformers for language understanding”. In: arXiv preprint arXiv:1810.04805 (2018).

Kaiming He et al. “Deep residual learning for image recognition”. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2016, pp. 770–778.

Antreas Antoniou, Harrison Edwards, and Amos Storkey. “How To Train Your MAML”. In: ICLR (2018).

Xingyou Song et al. “ES-MAML: Simple Hessian-Free Meta Learning”. In: International Conference on Learning Representations. 2020. URL: https://openreview.net/forum?id=S1exA2NtDB

Alex Nichol, Joshua Achiam, and John Schulman. “On first-order meta-learning algorithms”. In: arXiv preprint arXiv:1803.02999 (2018).

Bradly Stadie et al. “The importance of sampling in meta-reinforcement learning”. In: Advances in Neural Information Processing Systems 31 (2018).

Risto Vuorio et al. “Multimodal model-agnostic meta-learning via task-aware modulation”. In: Advances in Neural Information Processing Systems 32 (2019).

Aniruddh Raghu et al. “Rapid Learning or Feature Reuse? Towards Understanding the Effectiveness of MAML”. In: ICLR. 2020.

Gregory Koch, Richard Zemel, Ruslan Salakhutdinov, et al. “Siamese neural networks for one-shot image recognition”. In: ICML deep learning workshop. Vol. 2. Lille. 2015.

Han Hu et al. “Relation Networks for Object Detection”. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). June 2018.

Matthias De Lange et al. “A continual learning survey: Defying forgetting in classification tasks”. In: IEEE transactions on pattern analysis and machine intelligence 44.7 (2021), pp. 3366–3385.

Valentin Vielzeuf et al. “Centralnet: a multilayer approach for multimodal fusion”. In: Proceedings of the European Conference on Computer Vision (ECCV) Workshops. 2018, pp. 0–0.

Adam Paszke et al. “Pytorch: An imperative style, high-performance deep learning library”. In: Advances in neural information processing systems 32 (2019).

Thomas Wolf et al. “Huggingface’s transformers: State-of-the-art natural language processing”. In: arXiv preprint arXiv:1910.03771 (2019).

Tristan Deleu et al. “Torchmeta: A meta-learning library for pytorch”. In: arXiv preprint arXiv:1909.06576 (2019).

Diederik P Kingma and Jimmy Ba. “Adam: A method for stochastic optimization”. In: arXiv preprint arXiv:1412.6980 (2014).

Nitish Srivastava et al. “Dropout: a simple way to prevent neural networks from overfitting”. In: The journal of machine learning research 15.1 (2014), pp. 1929–1958.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 7
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Broader Impacts section (Appendix A)
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...

6
In this work we seek to develop better methods for few-shot learning. Few-shot learning has the potential to democratise access to powerful machine learning methods as it enables their usage in resource-constrained environments and minority groups which may not be well-represented in datasets which have largely been curated in western cultures. However, it could also have potential negative implications, for example, it could be used in facial recognition, reducing the privacy of individuals.

The dataset we release with this work (iNat-Anim) was developed to help evaluate multi-modal few-shot learning. It consists of less noisy, short textual descriptions than previous works [13]. This enables method development in the field with smaller models and therefore it could reduce the environmental impact of training large models for research purposes. While we inspected the data as much as possible, we have not checked all of the descriptions obtained from the Animalia website. There always remains a risk with using web-scraped data that harmful or biased descriptions could be present, and as such the data must be used with care.

### A Broader Impact

In this work we seek to develop better methods for few-shot learning. Few-shot learning has the potential to democratise access to powerful machine learning methods as it enables their usage in resource-constrained environments and minority groups which may not be well-represented in datasets which have largely been curated in western cultures. However, it could also have potential negative implications, for example, it could be used in facial recognition, reducing the privacy of individuals.

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### B Implementation Details

All models were implemented in PyTorch [34]. Each training run took 1.5 to 3 hours on a single free-tier Google Colaboratory GPU. We used BERT [22] (bert-base-uncased) from the Hugging Face library [35] as the pre-trained text encoder for all models. We followed the standard pre-processing routine for BERT, which involved truncating descriptions that were longer than the maximum sequence length for the model. We use ResNet-152 [23] as the pre-trained image encoder for all models. This has a feature dimension of 2048. The final layer (head) was fine-tuned but all other parameters were frozen during training.

The Torchmeta library [36] was used to construct meta-splits for the dataset. We used a 60:20:20 train:validation:test class splitting. Due to computational restrictions we could not perform extensive
hyperparameter tuning. Instead, hyperparameters were chosen via simple heuristics that maximized accuracy on the validation split, using suggestions from the literature as starting points. The validation split was also used to select the best model checkpoint using the validation loss. Our code has been open-sourced\footnote{https://github.com/s-a-malik/multi-few}. Poignant hyperparameters were as follows:

**AM3/Prototypical Networks**  We set the prototype dimension to 512, and used a single hidden layer neural network with hidden dimension 512 for each of the $g$ and $h$ networks. We found that the number of tasks per batch of 5, 3, 2 and 1 and query set size during training of 10, 8, 8 and 8 worked well heuristically for 1, 3, 5 and 10 shots respectively. In all cases, we used the Adam optimizer\footnote{https://creativecommons.org/licenses/by-nc/4.0/} with learning rate 0.001. Additionally, we used dropout with $p = 0.2$ and an L2 weight decay of 0.0005 to prevent overfitting. For the zero-shot AM3 model, we forced $\lambda = 0$ to remove dependence of the prototype on the support images. For the uni-modal prototypical network baseline\footnote{https://creativecommons.org/licenses/by-nc/4.0/}, we simply used our AM3 implementation but manually forced $\lambda = 1$, which removes the dependence of the prototype on the text.

**FuMI/MAML**  We use 4 tasks per batch, and a query set size during training of 32 for all shots. For both FuMI and MAML, the model consisted of three fully-connected layers, with hidden layer widths of 256 and 64. The FuMI hypernetwork also consisted of two fully-connected layers, with a hidden layer width of 256. A dropout rate of $p = 0.25$ was used. Again, we used the Adam optimizer with learning rate 0.00003 and an L2 weight decay of 0.0005 for outer-loop training. For the inner-loop, a step size of 0.01 was used, with 5 training updates on the support set at meta-train time. At meta-test time, 50, 50, 100 and 100 inner-loop updates were performed on the support set, for 1, 3, 5 and 10 shots respectively.

### C iNat-Anim Details

The images are a subset of the images from the iNaturalist 2021 CVPR challenge\footnote{https://iccv2021.org/iccv2021/} and have been augmented with textual descriptions of each species from Animalia\footnote{https://creativecommons.org/licenses/by-nc/4.0/}, an online animal encyclopedia. Full permission for website scraping and dataset publication was obtained from the owners of Animalia prior to release of the dataset. We place a CC BY-NC 4.0\footnote{https://creativecommons.org/licenses/by-nc/4.0/} licence on the textual descriptions scraped from Animalia, whilst retaining the per-image licensing from the relevant subset of iNaturalist. The descriptions are curated by the website owners and we manually inspected a significant proportion for quality. To best of our knowledge, the descriptions do not contain any personally identifiable or offensive material. Figure\footnote{https://creativecommons.org/licenses/by-nc/4.0/} shows the distributions of classes and description lengths across the dataset.

![Figure 3: The left pane shows the distribution of species in iNat-Anim across birds, reptiles and mammals. The right pane shows a histogram of the number of words in each description of each species.](image-url)