**Low-Shot Learning from Imaginary Data**

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**Motivation**
- Problem statement: low-shot learning
- Key insight: leverage structure of the visual world
  - Modes of variation are shared across classes
  - Humans can visualize a novel object in other poses or surroundings
- Our approach: an end-to-end model that "hallucinates" novel training samples
  - Hallucination criterion: produces examples useful for classification
  - Training hallucinator with meta-learning: jointly optimizes a meta-learner [1] with a hallucinator

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**Meta-Learning with Learned Hallucination**
- A general framework: agnostic to meta-learning algorithms
- Hallucinator: parametric function \( h(x, z) \)
- Meta-training the hallucinator
  - Augmented training set \( \mathcal{S}_{aug} \)
  - End-to-end training: \( G \) along with \( h \)
- Benefits of end-to-end training
  - Directly produces hallucinations useful for class distinctions
  - Makes allowance for any errors in the hallucination
  - No extra annotation & no heuristics

(Hallucination is performed in feature space; images shown for illustration)

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**Experiment Protocol**
- Tradeoffs between base and novel classes in joint evaluation: a novel class prior \( p \)
- A new evaluation: top-5 accuracy
  - In only-novel label space
  - In only-base label space
  - In joint label space without and with a cross-validated \( p \)

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**Meta-Learning**
- Setup: learn from a meta-set—a collection of low-shot classification tasks
- Meta-training: train a classification algorithm \( h \) on small \( \mathcal{S}_{aug} \) that achieves high accuracy on \( \mathcal{D} \) for different tasks on \( \mathcal{D}_{base} \)
- Meta-testing: use \( h \) to solve novel classification tasks on \( \mathcal{D}_{base} \)

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**ImageNet low-shot classification**

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**Unpacking the Performance Gain**
- Sophisticated hallucination architectures are necessary
- Meta-learning the hallucinator is necessary
- Diverse samples are processed

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**Visualizing the Learned Hallucinations**
- t-SNE visualizations: on novel classes for prototypical networks
- Our hallucinator vs. baseline Gaussian hallucinator: match the class distributions more closely & with different seed examples capture different parts of the space
- Clustering around the class boundaries: perhaps a consequence of discriminative training of the hallucinator

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**Conclusion and Future Work**
- Low-shot learning that uses a hallucinator to generate additional examples and trains the hallucinator end-to-end with meta-learning
- Significant gains irrespective of meta-learning approaches
- Future work: pin down exactly the effect of the hallucinated examples & increase the diversity of the hallucinations

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**References**