One Shot Learning via Compositions of Meaningful Patches

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motivation

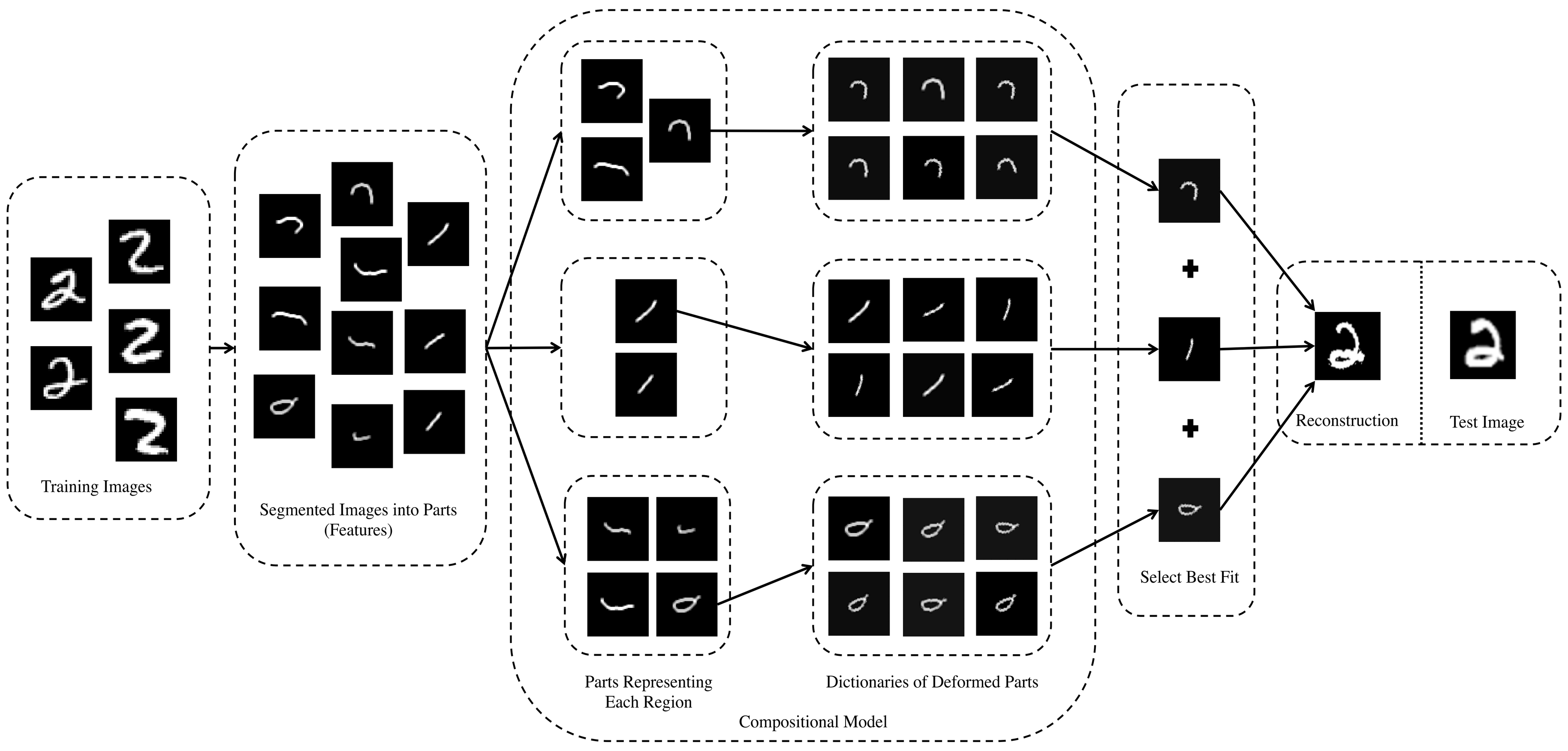
Current state-of-the-art algorithms perform very well on most common datasets **when trained on thousands of examples**
However, humans are able to **learn a concept from very few examples, perhaps even just one**

what is one shot learning?

One shot learning is an object categorization task where very few examples (1-5) are given for training

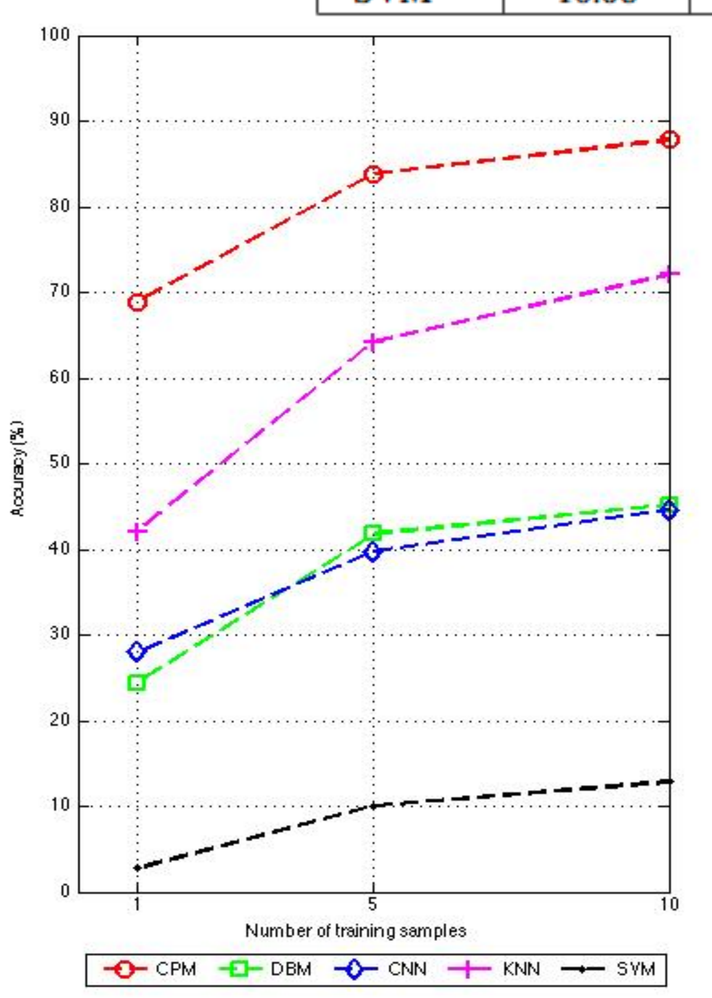
our approach

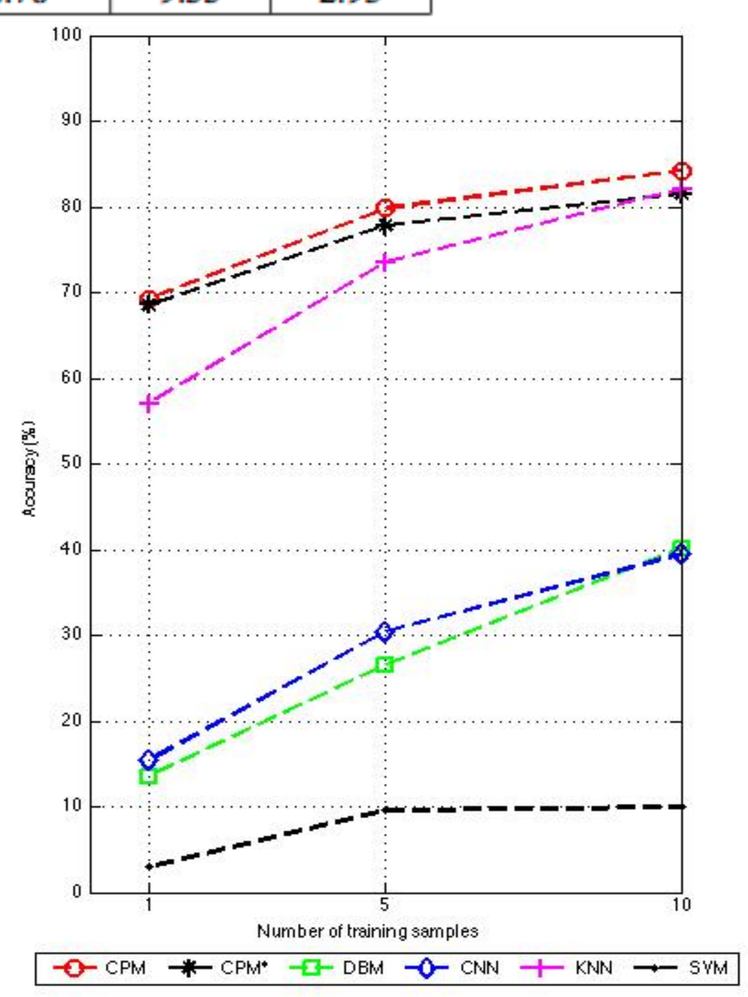
- Learn a meaningful patch-based representation of the underlying structure of an object without human supervision
- Build a compositional model composed of a set of compact dictionaries of meaningful patches
- Reconstruct the target image with deformations of the meaningful patch dictionaries by patch matching
- Select the class of the best proposed reconstruction as label



experimental results

Method	MNIST n=5	MNIST n=1	USPS n=5	USPS n=1
CPM	**83.79**	**68.86**	**79.88**	**69.31**
CPM*	-	-	77.81	68.58
DBM	41.76	24.37	26.60	13.56
CNN	39.80	28.01	30.42	15.37
K-NN	64.26	42.08	73.59	56.98
SVM	10.08	2.78	9.55	2.93





conclusion

- Our compositional model outperforms popular algorithms on the recognition task under one shot learning
- The extracted features are semantically meaningful
- The model generalizes beyond the training set and demonstrates transferability between separate datasets

acknowledgements

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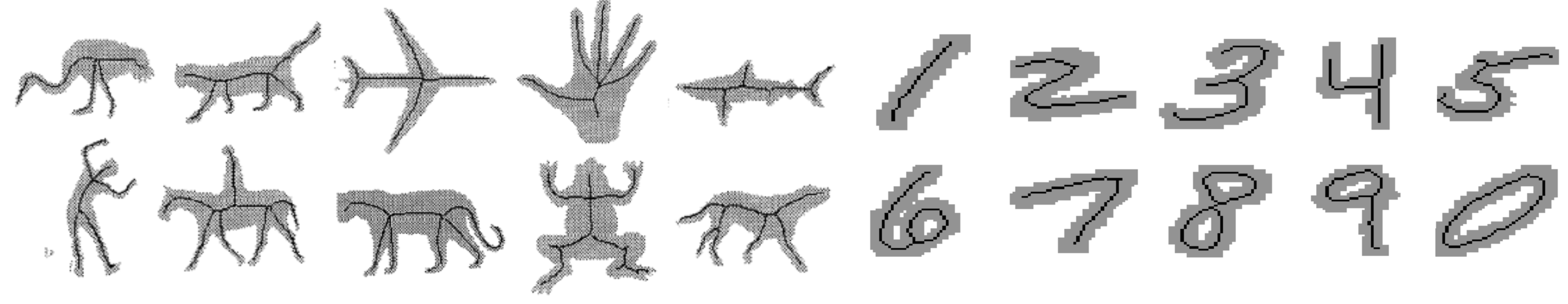
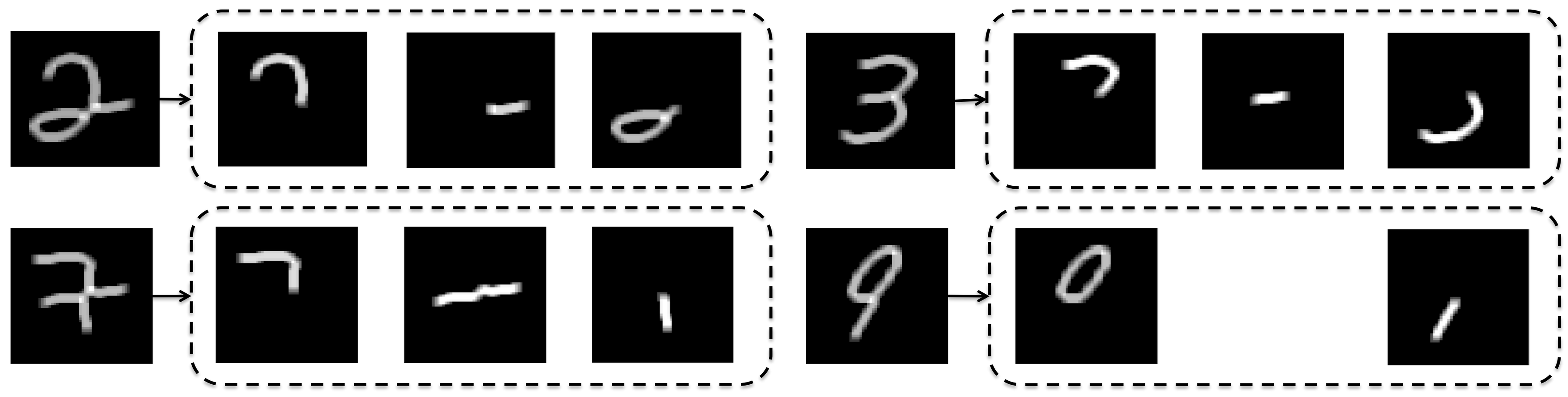
feature extraction

- Symmetry axis acts as a robust object descriptor



- Branch points separate one meaningful part from another
- Small segments are merged with nearby meaningful parts

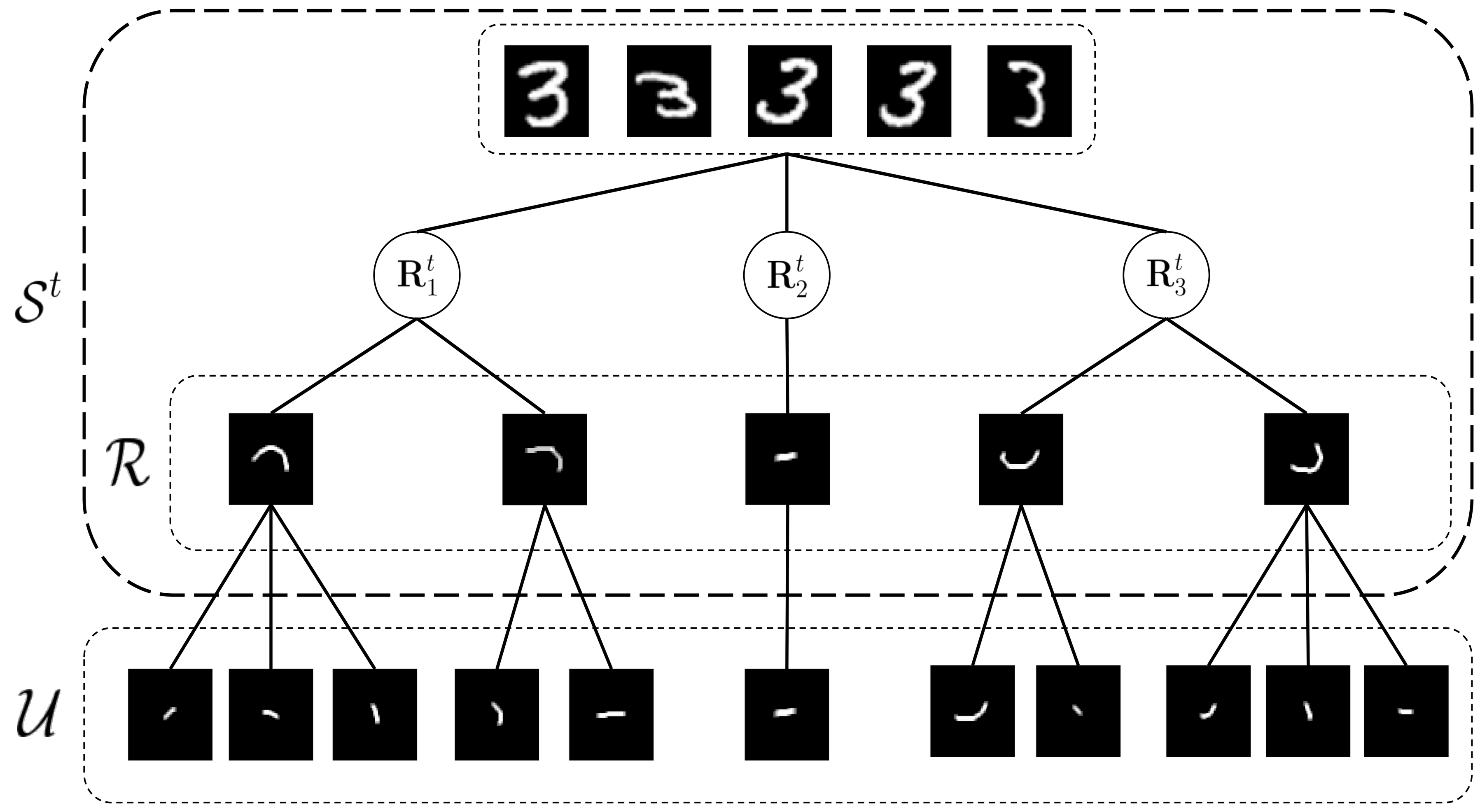


compositional model

- Similar parts, defined by a high match score via Normalized Cross Correlation, are merged to create a compact dictionary
- An AND-OR graph of the part relations is construction for m patches for samples t and u:

$$\mathbf{S}^t = (\mathbf{R}_1^t \vee \mathbf{R}_1^u)\wedge\ldots\wedge\mathbf{R}_k^t\wedge\ldots\wedge(\mathbf{R}_m^t \vee \mathbf{R}_m^u)$$

- Deformations are applied to the meaningful patches



sample reconstructions

*left image denotes test image, right image denotes reconstruction