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COL 774: Assignment 4 (Semester I, 2021-22)

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1 Introduction and Problem Formulation

The Analogical Reasoning Dataset from the paper **'Solving Visual Analogies using Neural Algorithmic Reasoning'** is given. The aim to to formulate it as a meta learning problem. Conditional Neural Processes (CNP)[2], Matching Networks (MAN)[3], Model-Agnostic Meta-Learning (MAML)[1] are three of the meta learning algorithms which will be applied on this dataset. Taking a look at the piece of code, we can see each of the namedtuple 'Problem' is a task, and for both meta train and meta test we have:

- (Problem.example.input, Problem.example.solution) = (X_train,y_train)
- (Problem.query, Problem.solution) = (X_test,ytest)

As shown in Fig [1], there are 6 examples in the training data and 4 options. Let's try to understand the method taking one example image into consideration. As shown against one example image, we have 4 option images. We take the pixel difference between the example image and the 4 option images. We call these differences as 'modified input' to the model. We perform a binary classification on these modified inputs where 1 indicates that the corresponding option image is the solution to the example image, 0 indicates otherwise. For example, in the first row of Fig [1], the solution is 2 i.e., the difference between example image and third option image is classified as 1 and all the rest classified as 0. By repeating this process for all the 6 training images, we get 24 modified inputs for each of the tasks. By doing so, We are using pixel difference of the example image and the option image to approximate the image transformation.

2 Method to run the Jupyter Notebook

- The Jupyter Notebook has 8 headers.
- Generate your kaggle API token and drag the 'kaggle.json' into the files tab in google colab.
- Run the **'Getting Kaggle NAR Dataset'**, it will download the dataset. You need to do this once for a single runtime on google colab.
- Run the **'AnalogicalReasoningDataset'** to get the dataset in usable form.
- Leave the **'Extras'**, it was only to understand and visualise the Analogical Reasoning Dataset.
- Run **'Global Imports'**.
- Once you run **'Global Imports'**, you can run any of the **'CNP'**, **'MAN'**, **'MAML'** headers i.e., models independently or one after another.

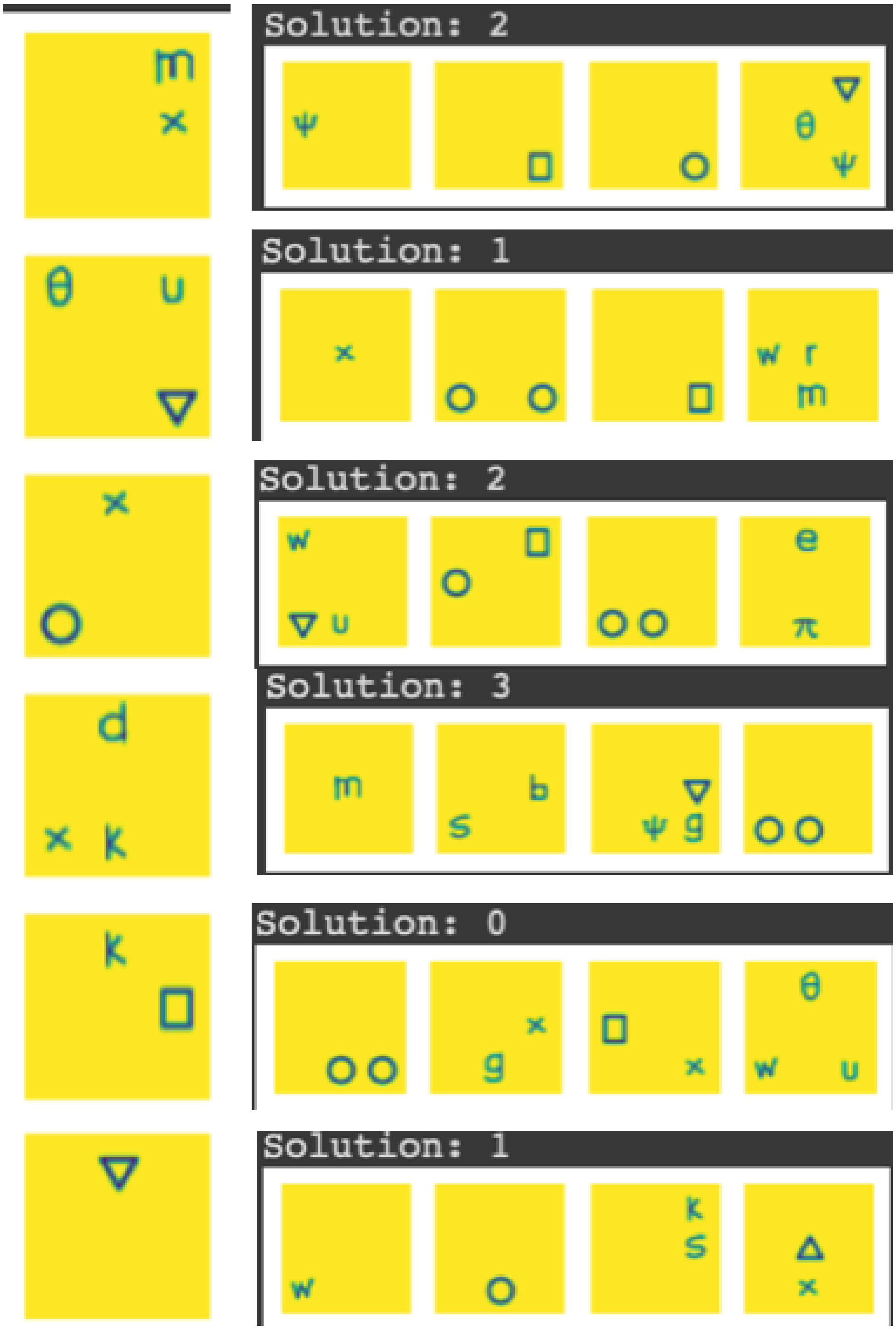

Figure 1: Training images and corresponding options

3 Analysis

The accuracy, loss, time taken is given in table and graphs are shown in Fig [3].

	NON OVERLAPPING				
	Num_tasks	num_epochs	Meta train Accuracy	Meta test accuracy	Time taken
CNP	50	50	0.76	0.51	53.81
	100	50	0.91	0.66750	97.307
	200	50	0.87	0.65125	191.766
	300	50	0.85	0.64	273
MAN	50	50	0.92	0.75	59.382
	100	50	0.9	0.745	114.101
	200	50	0.87875	0.743	229.469
	300	50	0.863	0.737	331.93
MAML	50	30	0.945	0.645	59.829
	100	30	0.91	0.65250	119.095
	200	30	0.9	0.64	242.5
	300	30	0.9	0.63	331.93

Figure 2: Table 1

4 Observation

- Here the task is overtly complicated but no of examples to compute each of the transformation is very less. Hence all the three models show signs of overfitting as apparent from the huge gap in the training and test error.
- Overfitting was more when num_epochs are large. Hence, I set num_epochs for CNP and MAN to be 50 and for MAML to be 30 (as it was taking lot more time for training especially when the num_task was large).
- Training time could probably be reduced by efficiently trying to fetch the data for each task.
- As number of tasks increasing, the accuracy decreases a bit which could be due to the diversity that is there in the range and complexity of transformation of the images as we sample more tasks.
- From the fourth graph in Fig [3], we see the extent of overfitting is relatively less in MAN.

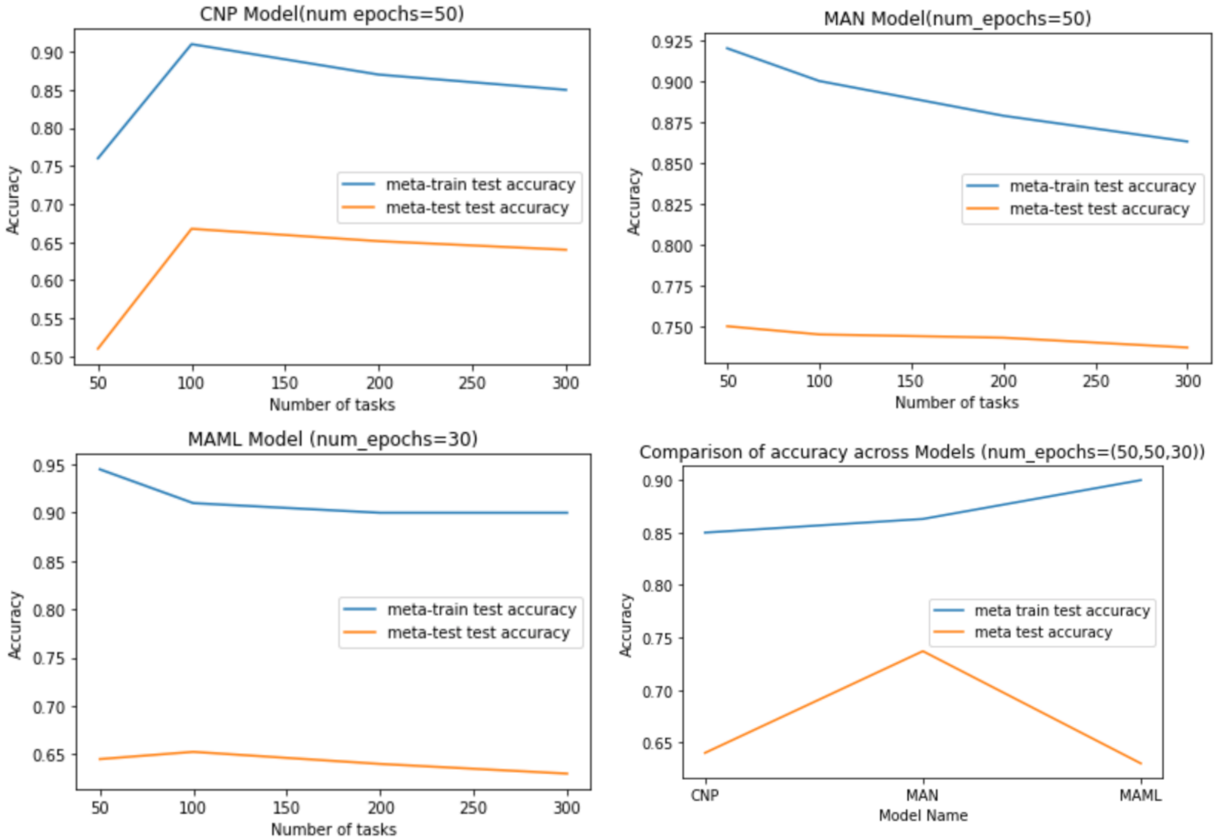

Figure 3: Accuracy of the three models

References

[1] FINN, C., ABBEEL, P., AND LEVINE, S. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of the 34th International Conference on Machine Learning - Volume 70* (2017), ICML'17, JMLR.org, p. 1126–1135.

[2] GARNELO, M., ROSENBAUM, D., MADDISON, C., RAMALHO, T., SAXTON, D., SHANAHAN, M., TEH, Y. W., REZENDE, D., AND ESLAMI, S. M. A. Conditional neural processes. In *Proceedings of the 35th International Conference on Machine Learning* (10–15 Jul 2018), J. Dy and A. Krause, Eds., vol. 80 of *Proceedings of Machine Learning Research*, PMLR, pp. 1704–1713.

[3] VINYALS, O., BLUNDELL, C., LILLICRAP, T., KAVUKCUOGLU, K., AND WIERSTRA, D. Matching networks for one shot learning. In *Advances in Neural Information Processing Systems* (2016), D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett, Eds., vol. 29, Curran Associates, Inc.