

1 We thank all the reviewers for their helpful feedback and positive view of our work. To address the re-
 2 viewers concerns (**R3,R4,R5**), we have added a comparison to Duan et al.’s One Shot Imitation learning in
 3 Tables 3 and 2, a comparison to a non-normalized TECNet ablation, as well as an evaluation on a Viz-
 4 Doom navigation task in Table 1. We believe that these additions address all of the main reviewer concerns.

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6 **R3,R5** *Lacking some important references on learning using task embeddings / goal representations, etc* Thank you
 7 for the pointers to more related work; missing these was
 8 an oversight. Hausman et al. is discussed at line 95 of the
 9 paper, and we will add discussion of the additional papers,
 10 as well as the language HRL paper from R3, in the related
 11 work section. Combining CPVs with natural language task
 12 descriptions is an interesting avenue for future work.

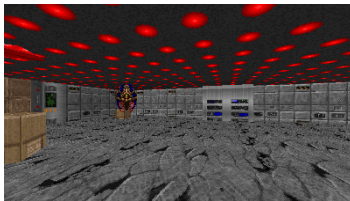
14 **R5** *TECNet normalizes the embedding. Is the embedding
 15 normalized in the same way in your model?* We do not
 16 normalize the CPV embeddings. To tease apart the effects
 17 of normalization, we have added a comparison to non-
 18 normalized versions of TECNet, which are labeled “TE”
 19 (task embedding) in Table 3 and 2.

20 **R4,R5** *More Comparisons.* We have added a comparison
 21 to Duan et al.’s One shot imitation method. As the authors
 22 have not released an implementation of the method or en-
 23 vironment, we implemented the key details of the method:
 24 the reference demonstration is encoded with a residual 1D
 25 convolution, and the LSTM policy attends over the refer-
 26 ence trajectory. This and the TE comparison will be run on
 27 the VizDoom env for the camera ready version.

28 **R4, R5** *Lack of motivation behind introducing new environ-
 29 ments.* We agree that benchmark environments are ideal for
 30 the integrity of the field. To address this, we have added a
 31 navigation task from VizDoom. Unfortunately, most cur-
 32 rently available environments are too simple to benefit from
 33 a compositional representation of tasks. The environment
 34 in Duan et al. was not made public. The environment
 35 from Sohn et al. was only released this summer (after the
 36 deadline). We are releasing our environments publicly with
 37 documentation, training code, and demonstration data.

38 **R5** *How does CPV compare to other imitation learning
 39 algorithms such as Behavioral Cloning, Dagger, or GAIL?* CPV can be used in conjunction with any imitation learning
 40 algorithm. In our results we use behavioral cloning, and we plan to try IRL methods such as GAIL in future work.

Figure 1: First person view in Viz-
 Doom env. The agent must navi-
 gate through multiple waypoints.



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Table 1: **VizDoom Navigation Results.** We evaluate our method in ViZDoom where the goal is to visit waypoints in a predetermined order. The actions are “turn left,” “turn right,” and “go forward.” The observation space consists of a first person image observation as well as the locations of the waypoints. We evaluate on trajectories that must visit 1 or 2 waypoints (skills), and also evaluate on the compositions of these trajectories. The policies were only trained on trajectories that visit up to 3 waypoints. All numbers are success rates of arriving within 1 meter of each waypoint.

MODEL	1 SKILL	2 SKILLS	1+1	2+2
NAIVE	97	94	36.7	2
TECNET	96	95.3	48.3	0
CPV	93	90.7	91	64

Table 2: **3D Pick and Place Results.** We added the TE and TE-Pair baselines, which use a task embedding like TECNet but without normalizing to the unit ball. TE-Pair has a triplet margin loss so that embeddings of the same task should be close in feature space, which is like the TECNet margin loss. The plain TE only uses the imitation learning loss. While TE performs well at the training tasks in this environment, it does not succeed at compositions of tasks. The Duan et al. architecture fails in this environment.

MODEL	1 SKILL	2 SKILLS	1,1
TECNET	82 ± 6	50 ± 2	33 ± 4
CPV	87 ± 2	55 ± 2	52 ± 2
TE	91 ± 2	55 ± 5	22 ± 2
TE-PAIR	81 ± 11	51 ± 8	15 ± 3
DUAN ET AL.	6 ± 1	0 ± 0	0 ± 0

Table 3: **2D crafting results.** The TE ablation, which is like TECNet but with un-normalized embeddings performs worse than TECNet. The Duan et al. architecture performs well in this crafting environment.

Model	4 Skills	8 Skills	16 Skills	2,2	2,2,2,2	4,4
TECNet	50 ± 14	39 ± 5	8 ± 11	52 ± 15	17 ± 5	34 ± 22
CPV	65 ± 10	80 ± 3	44 ± 9	55 ± 5	29 ± 9	58 ± 8
CPV-Hom.	84 ± 12	82 ± 15	54 ± 8	71 ± 1	29 ± 10	48 ± 14
TE	29 ± 4	21 ± 29	3 ± 2	35 ± 10	20 ± 12	15 ± 7
TE-Pair	25 ± 6	12 ± 2	0 ± 0	36 ± 9	10 ± 3	12 ± 4
Duan et al.	75	67	80	59	62	66