## An Interactive Navigation Method with Effect-oriented Affordance

## Supplementary Material

## 6. Study of Affordance Prediction

In Table 4, we present the results of our affordance functions on the static dataset(100k training samples, 10k validation samples, 10k testing samples). Note that we spawn different sets of obstacle assets (same 20 categories, different styles and appearances) in different scenes when splitting the datatset. Thus, the affordance model is tested with zero-shot environments and objects. For effect affordance, we round the time cost prediction to a binary value to see if the model can approximately estimate whether an obstacle can be removed with interaction. The results in Table 4 show that our affordance model maintains considerable accuracy when facing zero-shot scenarios. Also the consistently limited performances on predicting *pickable* and carrying out *PickUp* in Table 3 confirm the significance of affordance predicting on action planning. We will update the results in our revised paper.

In Figure 6, we present two qualitative examples emphasizing the significant roles of object affordance (OA) and pose affordance (PA) in specific scenarios:(a) Predicting the laptop as *pickable* helps the planner choose the correct interaction, instead of try invalid actions and get stuck. (b) Predicting a negative pose affordance helps the agent avoid taking interactions at invalid poses (e.g. far from objects, out of view). Please refer to Figure 3 (body part) to see the example showing the significance of effect affordance (EA).

Affordances	Precision			Recall			F1		
	train	val	test	train	val	test	train	val	test
pushable	81.5	79.4	79.2	76.6	73.9	72.0	78.8	76.5	75.4
pickable	69.1	69.5	65.0	73.2	72.5	66.8	70.9	71.0	65.2
	93.7								
effect (time cost)	75.7	79.2	78.7	89.3	87.8	79.8	81.9	83.3	79.3

Table 4. Affordance prediction results on static dataset.

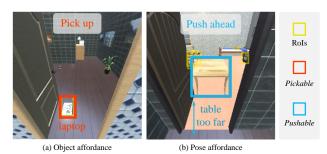


Figure 6. Qualitative examples where two affordance components play important roles.