

# Technical report on AGLI

In this report, we discuss the parameter sensitivity. We evaluate the effect of the embedding dimension size  $d$  and the activation threshold  $\epsilon$  on the performance of AGLI. Due to the long training time on Yelp and ML1M, we only conduct experiments on DBLP and AMms in the early stages. The experimental results on both Yelp and ML1M datasets will be complemented in the future.

## 1 Embedding Dimension size

Embedding dimension size  $d$  means the length of the generated node embedding, where each dimension in node embedding represents a value. Combining values of fixed lengths can express the important information contained in the network.

In this section, we will fix the other parameter settings and choose different values for  $d$  such as 32, 64, 128, 256, 512 to test the performance on AGLI and baselines. We evaluate these methods on node classification task and use Accuracy as metrics.

**Table 1.** Parameter sensitivity experiment of embedding dimension size  $d$

Accuracy	method	d=32	d=64	d=128	d=256	d=512
DBLP	DeepWalk	0.5990	0.6057	<b>0.6140</b>	0.6129	0.6051
	node2vec	0.6212	0.6246	<b>0.6249</b>	0.6207	0.6249
	GraphSAGE	0.6239	0.6303	0.6331	<b>0.6340</b>	0.6305
	HTNE	0.6136	0.6255	<b>0.6347</b>	0.6328	0.6337
	JODIE	0.6209	0.6233	<b>0.6259</b>	0.6203	0.6187
	AGLI	0.6392	0.6399	<b>0.6407</b>	0.6407	0.6398
AMms	DeepWalk	0.5660	0.5757	<b>0.5780</b>	0.5711	0.5697
	node2vec	0.5612	0.5646	<b>0.5772</b>	0.5707	0.5749
	GraphSAGE	0.5685	0.5687	<b>0.5763</b>	0.5759	0.5703
	HTNE	0.5736	0.5743	0.5767	0.5728	<b>0.5768</b>
	JODIE	0.5680	0.5703	<b>0.5755</b>	0.5744	0.5731
	AGLI	0.5902	0.5911	<b>0.5911</b>	0.5909	0.5907

According to Table 1, we find that the embedding size has little effect on the performance of AGLI and it performs the best overall. The results prove the robustness to embedding size of AGLI.

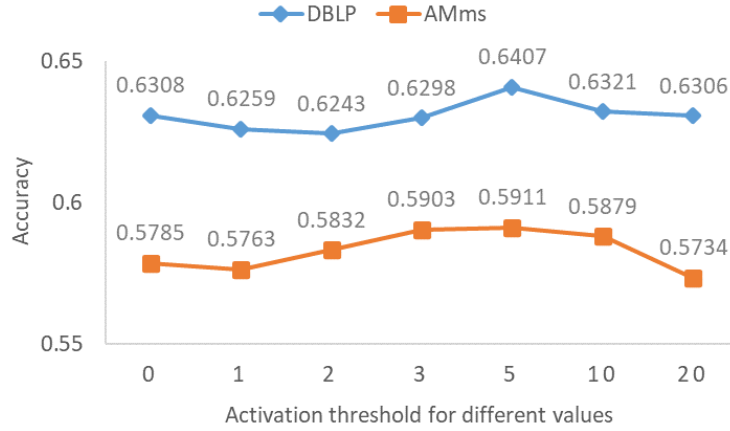
In addition, we can see almost all methods achieve the best performance when the node embedding size  $d=128$ . Where GraphSAGE works best when  $d=256$  on DBLP, HTNE works best when  $d=512$  on AMms. However, their results have a smaller difference compare with the perofrmance when  $d=128$ . We believe this is due to the acceptable error on different datasets. We can also see that GraphSAGE and HTNE achieve the best performance when  $d=128$  on another dataset. To our knowledge, most network representation learning

methods choose  $d=128$  as the default value for training. Therefore, we set the embedding dimension size  $d$  to be 128 on AGLI and use default values of  $d$  in baselines (In fact, all  $d=128$  of them).

## 2 Activation threshold

In the global network influence subsection, we propose an activation threshold  $\epsilon$  for all nodes.  $\epsilon$  is a hyper-parameter which determines whether global network environment changes will influence a node. Given a node  $u$ , if its cumulative affinity  $\epsilon_u$  exceeds the activation threshold,  $u$  will enter an active status. In the experiments, we set the value of the activation threshold  $\epsilon$  to 1 by default.

In this section, we will fix the other parameter settings and choose different values for  $\epsilon$  such as 0, 1, 2, 3, 5, 10 to discuss the effect of the activation threshold on AGLI.



**Fig. 1.** Parameter sensitivity experiment of activation threshold  $\epsilon$

According to Figure 1, we can see almost AGLI achieve the best performance when the activation threshold  $\epsilon=5$ . In addition, compare the performance difference of  $\epsilon=3$  and  $\epsilon=5$ , the difference on AMms is less than on DBLP. We believe this phenomenon is due to the following reasons. The average degree of each node in DBLP and AMms is 16.87 and 1.20, respectively. It means that nodes in DBLP have more neighbors than in AMms. Therefore, a node in AMms is more difficult than in DBLP to achieve a high activation threshold.