0.606
 0.18
 0.637
 0.052
 0.698
 0.49
 0.666
 0.685
 0.606
 0.19
 0.052
 0.052
 0.061

 0.603
 0.451
 0.425
 0.432
 0.001
 0.466
 0.015
 0.423
 0.402
 0.439
 0.011
 0.021

Table 2: Retrieval Results (• & \circ denote statistical significance at p-value < 0.01 & < 0.05 respectively)

Dataset	#QAs	t=5				t=50			
		Prec	SR	MAP	NDCG	Prec	SR	MAP	NDCG
stats	4004	0.016	0.076	0.057*	0.060	0.002	0.096	0.058	0.071
programmers	4107	0.020	0.096	0.068	0.075	0.002	0.115	0.069	0.088
wordpress	4744	0.019	0.091	0.069	0.074	0.002	0.112	0.070	0.085
physics	5044	0.025	0.120	0.088	0.094	0.003	0.148	0.090	0.111*
mathematica	5084	0.018	0.087	0.067	0.072	0.002	0.116	0.069	0.084
unix	5330	0.023	0.115	0.089	0.094	0.003	0.137	0.091	0.107*
gaming	6398	0.034	0.166	0.130°	0.137	0.004	0.189	0.132	0.155
english	6668	0.024	0.115	0.090	0.095	0.003	0.130	0.092	0.107*

0.061 2.041 2.72

 0.003
 0.038
 0.061

 0.002
 0.070
 0.025
 0.053

TTREM

Method

TBLM

AENT

TTRLW

0.39 0.67

Table 3: LASER-QA Results (Boldfacing and Statistical Significance indications from comparison with TopicTRLM and TBLM) over Larger Categories in CQADupStack

Figure 1: NDCG (Y-axis) v/s. k

creases way beyond the training neighborhood size (i.e., 15), LASER-QA is seen to deteriorate gracefully (as expected).

• LASER-QA performance peaks on rankaware metrics such as MAP and NDCG (even at t=50), indicating it's high effectiveness in producing relevant results at the top.

These observations underline the effectiveness of LASER-QA as a CQA retrieval method. It may be noted that LASER-QA uses compact representations (d < 2000), as compared to vocabulary space representations that are typically ≥ 5000 .

Trends at High t: The performance trends at high values of t are explained by the usage of the local neighborhood (of size k) in LASER-QA latent space learning. Going down the result list much beyond k reveals expected, but graceful, decline in accuracy. For automated processing scenarios that necessitate large t, a correspondingly high k may be used in learning. It is notable that LASER-

QA's focus on local neighborhood manifests as enhanced accuracy at the top of the result set.

LASER-QA Analysis on Larger CQADup-Stack Datasets: Owing to scalability issues of AENN that disallows a full evaluation over larger categories in CQADupStack, we present LASER-QA results over them in Table 3 to illustrate the consistency in trends. Boldfacing and statistical significance have the same semantics as earlier, with the comparison performed against only TopicTRLM and TBLM.

5.3 LASER-QA Parameter Analysis

We now analyze the NDCG trends (NDCG being the most popular IR metric) across LASER-QA parameters, i.e., k, α and d, varying each one separately keeping the default choice for others.

Varying k: Figure 1 plots NDCG against values of k from {5, 10, 15, 20}. As may be seen, the accuracy is seen to improve with increasing k in the lower ranges, while sat-