REAL-WORLD
DATASETS DISTRIBUTION

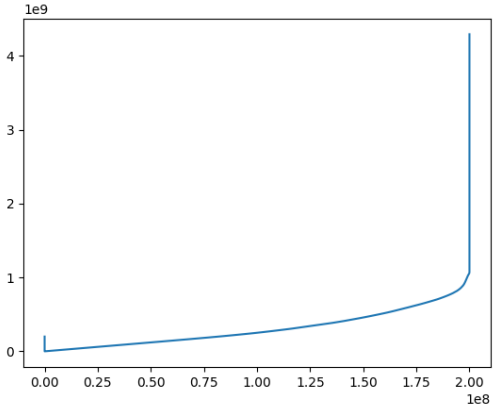


Figure 1: Amzn uint32

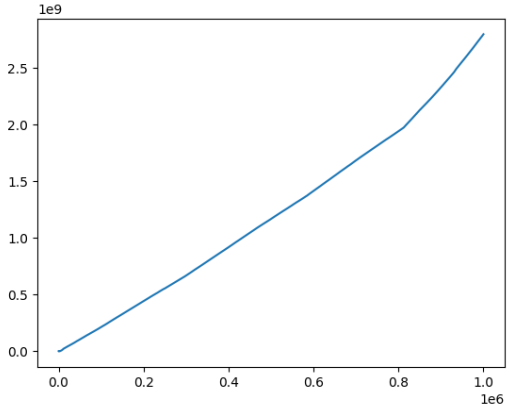


Figure 2: CompanyNet

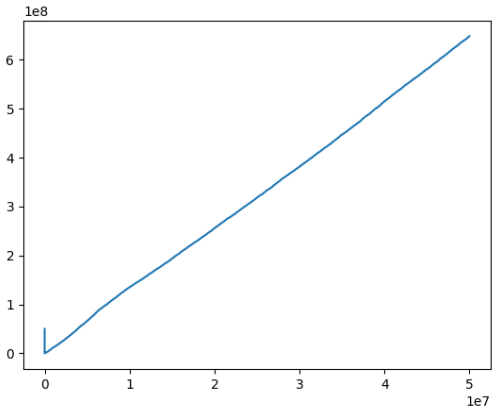


Figure 3: Friendster

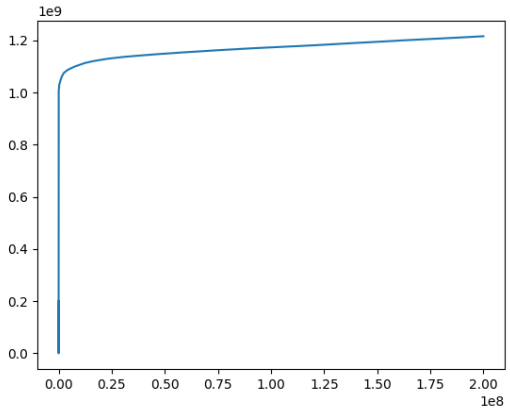


Figure 4: Wiki uint32

Real-world datasets - distribution. The x axis reports the indexes (positions) in the vector to store, while the y axis reports the corresponding values.

SYNTHETIC DATASETS
DISTRIBUTION

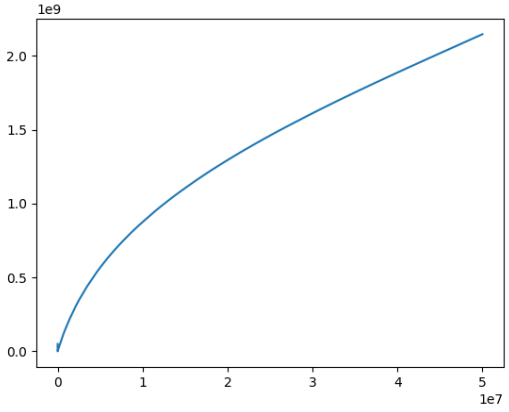


Figure 5: Normal

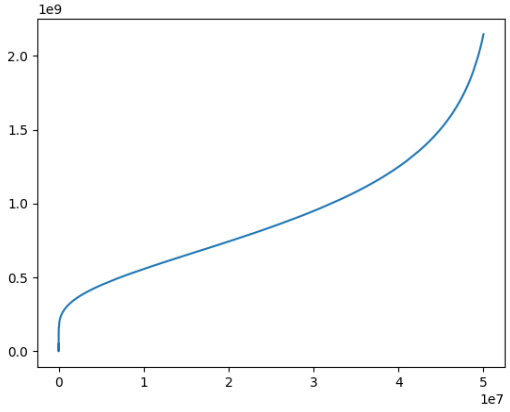


Figure 6: Lognormal

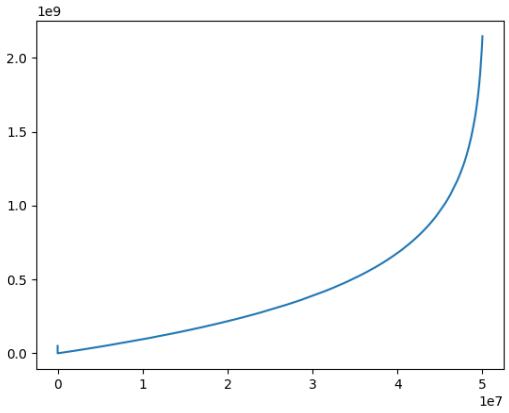


Figure 7: Exponential

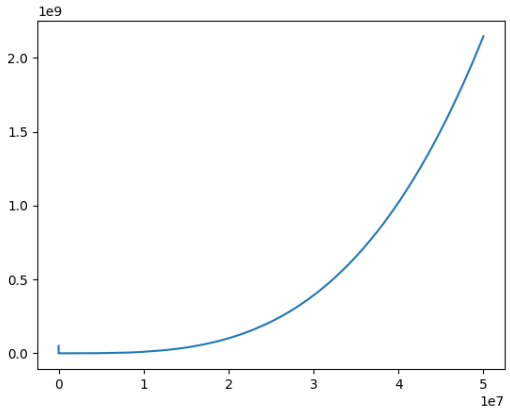


Figure 8: Zipf

Synthetic dataset - distribution. The x axis reports the indexes (positions) in the vector to store, while the y axis reports the corresponding values.

64-BIT DATASETS
DISTRIBUTION

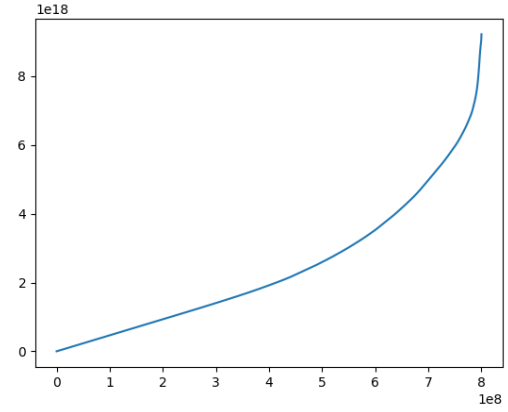


Figure 9: Amzn uint64

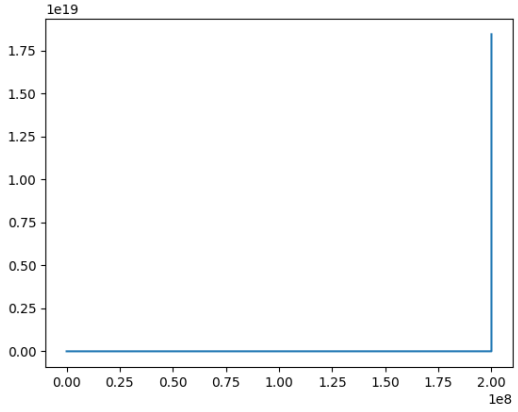


Figure 10: Facebook uint64

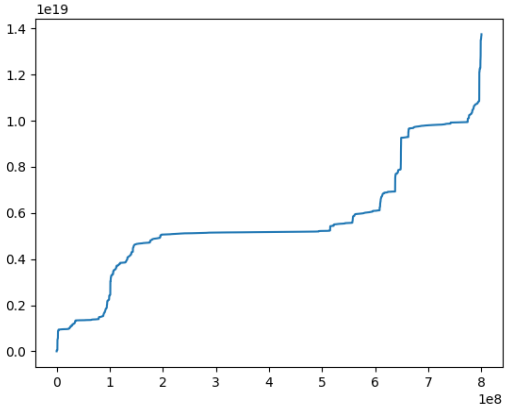


Figure 11: OSM Cellids uint64

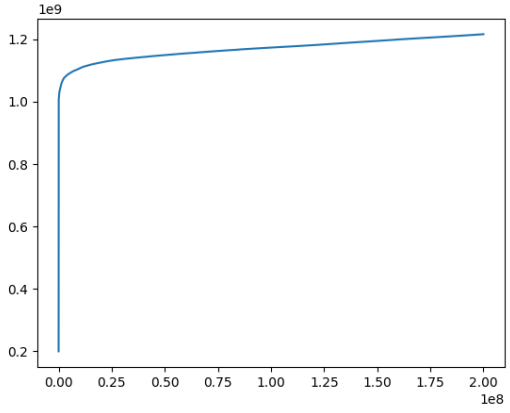
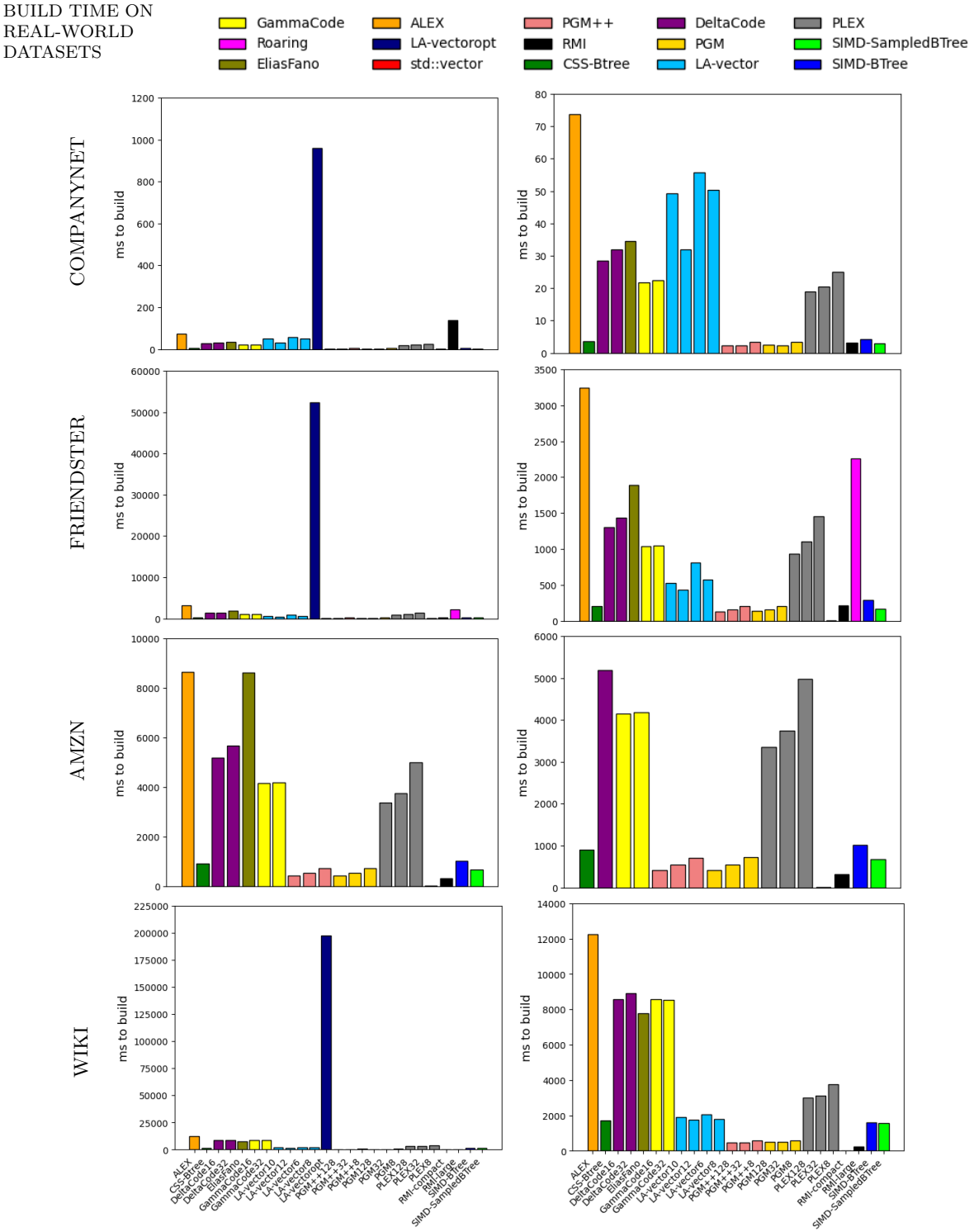


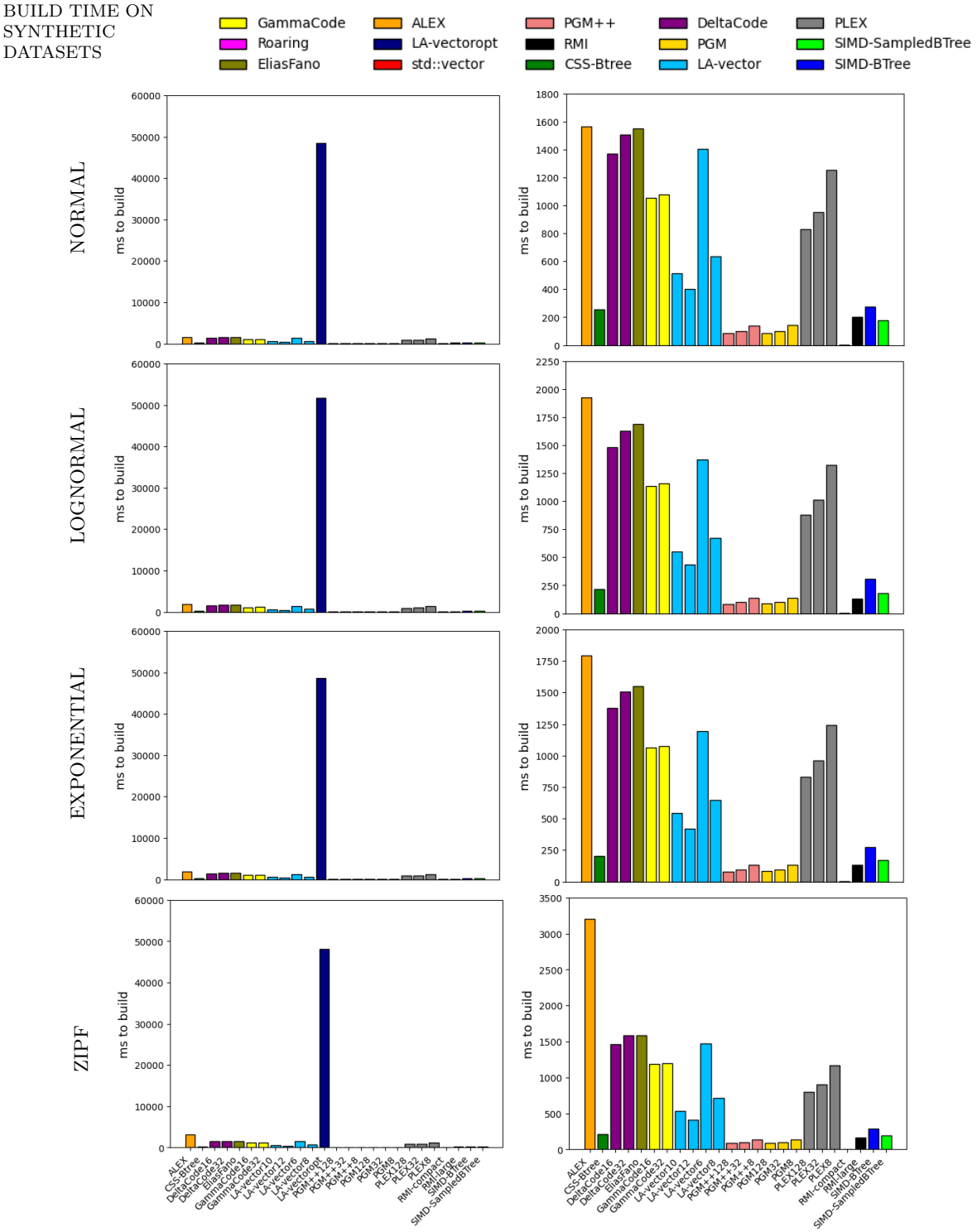
Figure 12: Wiki uint64

64-bits datasets - dataset distributions. The x axis reports the indexes (positions) in the vector to store, while the y axis reports the corresponding values.



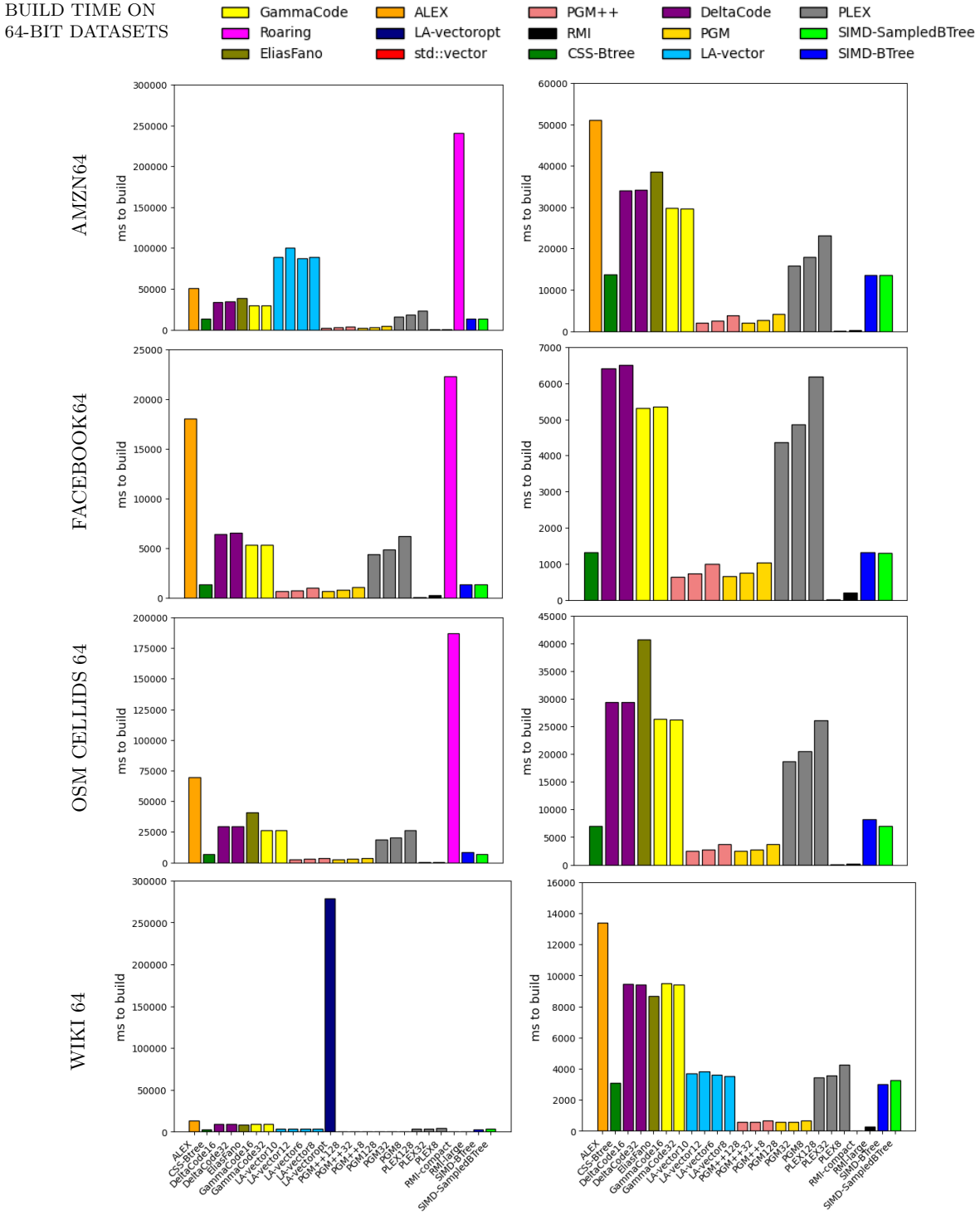
The plots above report the time required to build the data structures (indexes) on the real-world datasets. On the left, the dataset's name is shown; in the middle, the complete plot with all the times expressed in milliseconds; and on the right, the same plot but excluding the ones with excessive build times (those that are over double the average of all build times of all indexes).

Figure 13: Build time on real-world datasets



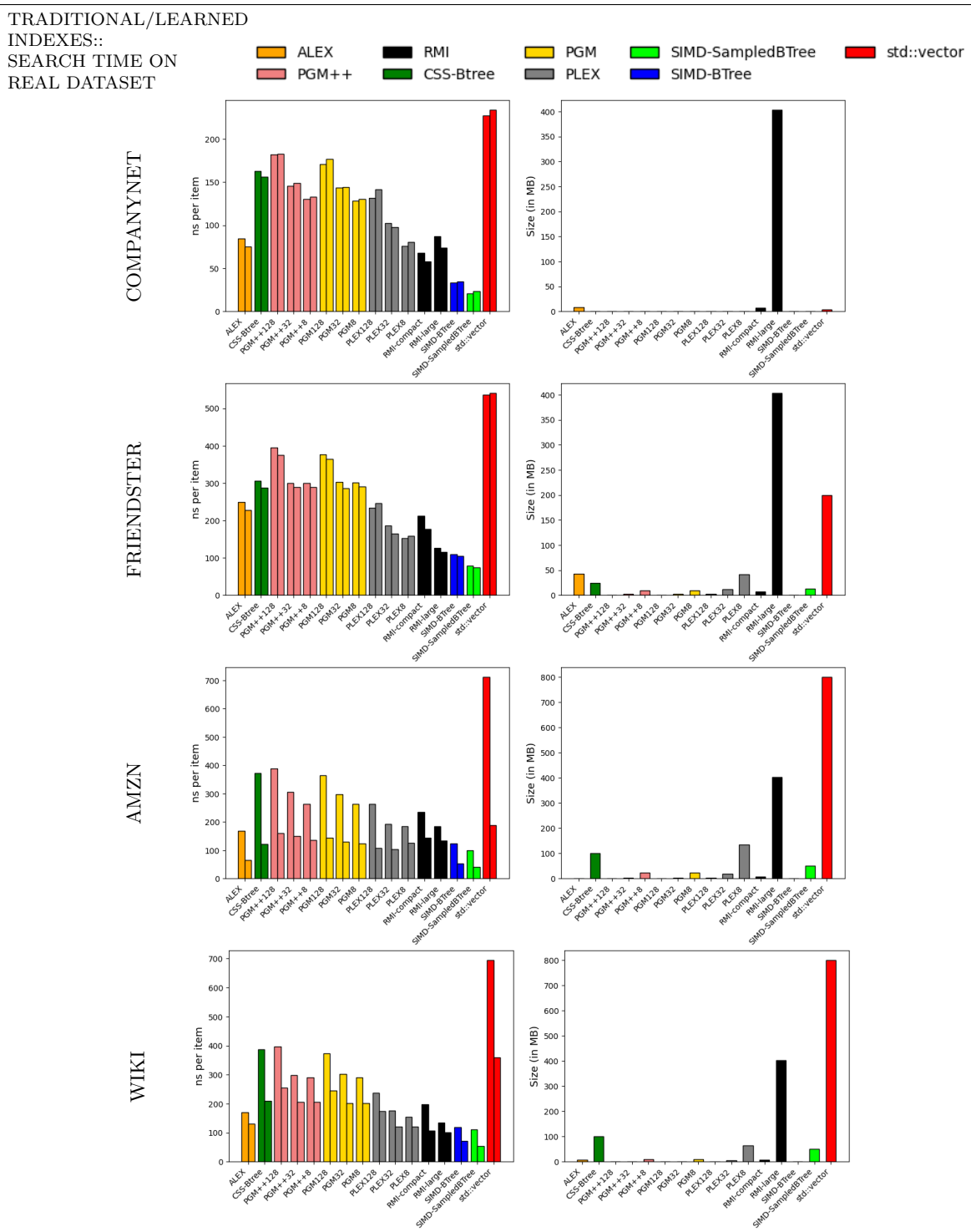
The plots above report the time required to build the data structures (indexes) on the synthetic datasets. On the left, the dataset's name is shown; in the middle, the complete plot with all the times expressed in milliseconds; and on the right, the same plot but excluding the ones with excessive build times (those that are over double the average of all build times of all indexes).

Figure 14: Build time on synthetic datasets



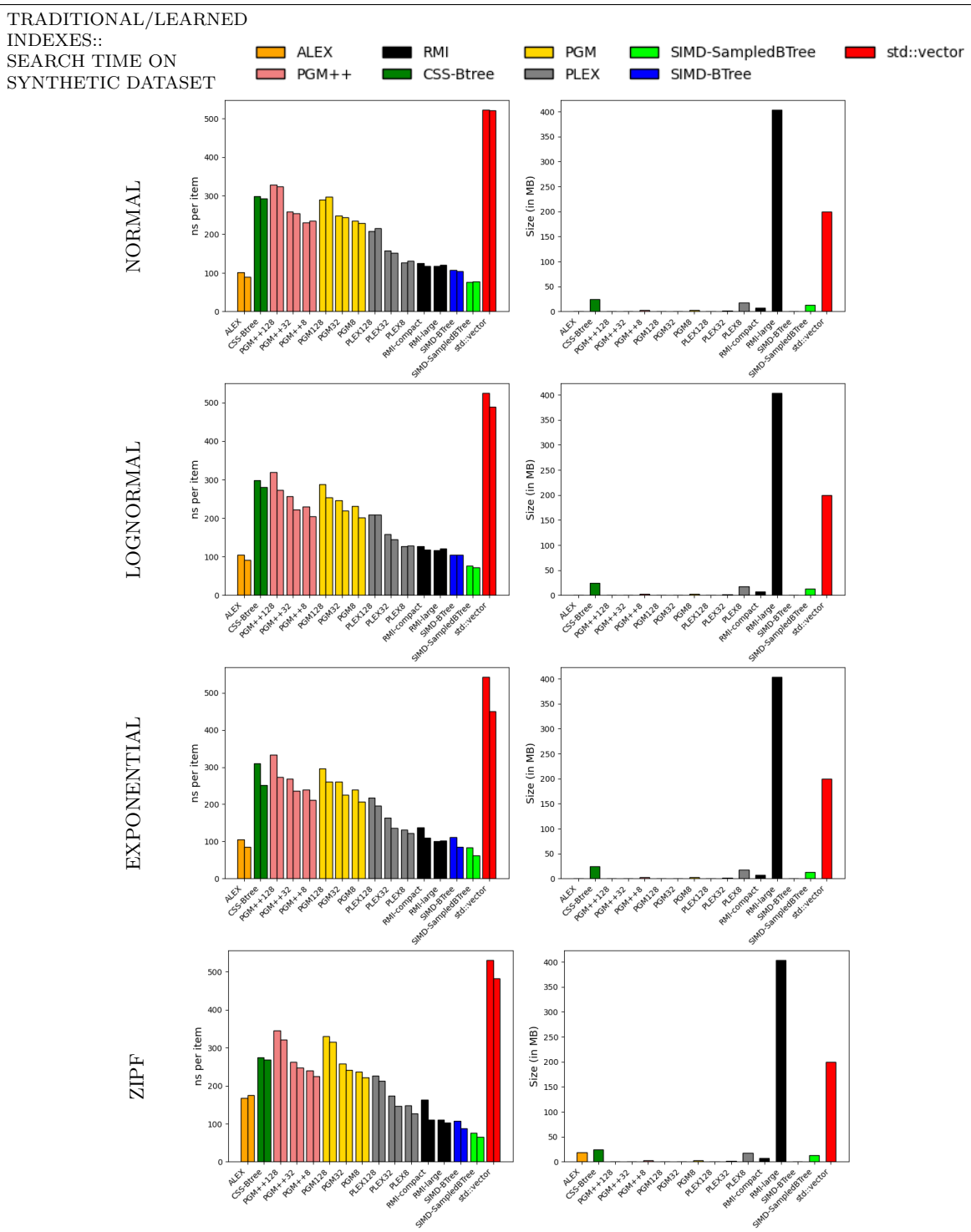
The plots above report the time required to build the data structures (indexes) on the 64-bit datasets. On the left, the dataset's name is shown; in the middle, the complete plot with all the times expressed in milliseconds; and on the right, the same plot but excluding the ones with excessive build times (those that are over double the average of all build times of all indexes).

Figure 15: Build time on 64-bit datasets



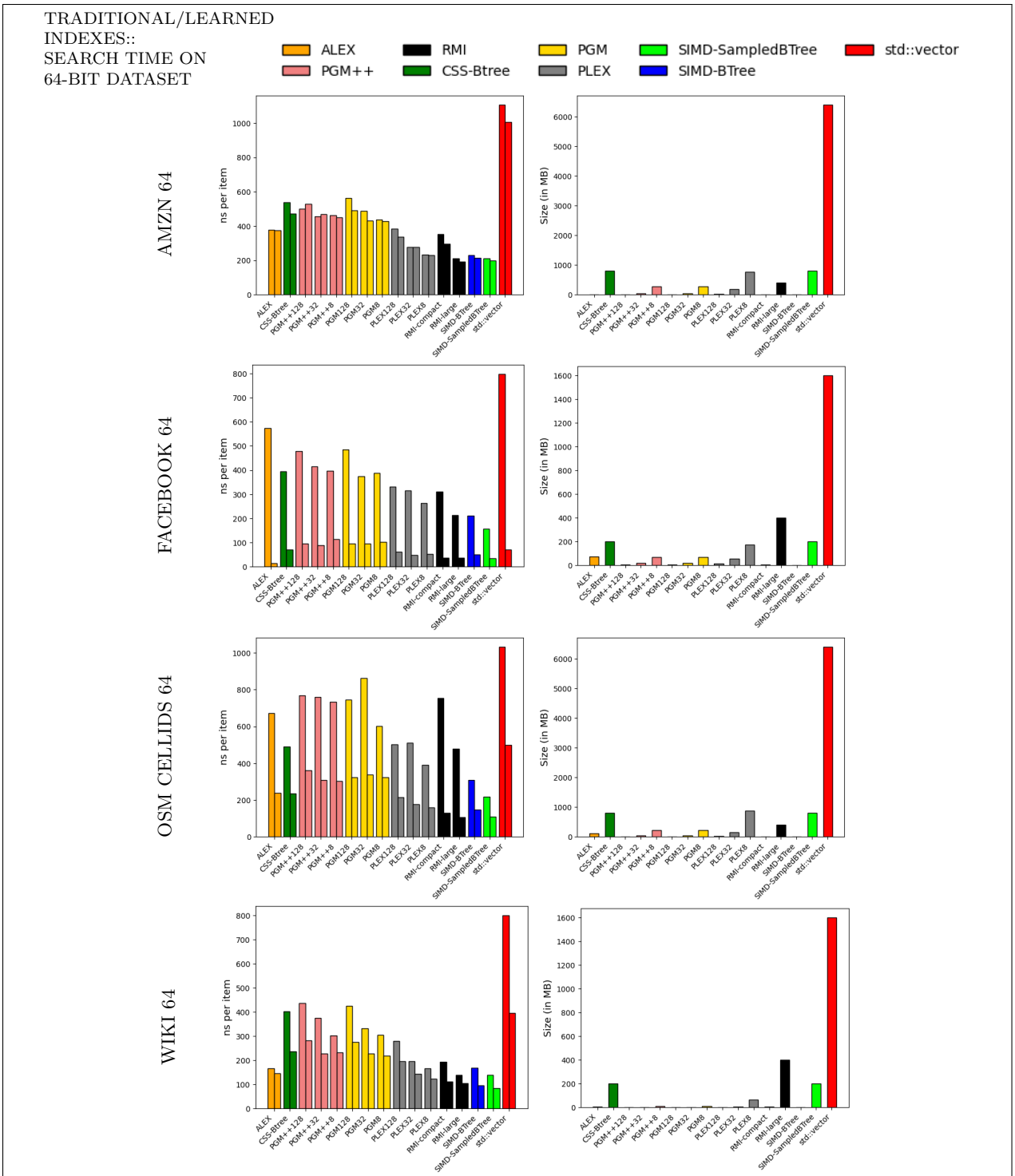
The performances of traditional and learned indexes on real-world datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot shows two bars for each data structure. The left/right one shows the average time to search for an existing/missing item in the collection.

Figure 16: Average time for pointwise queries on traditional and learned indexes, built on real-world datasets.



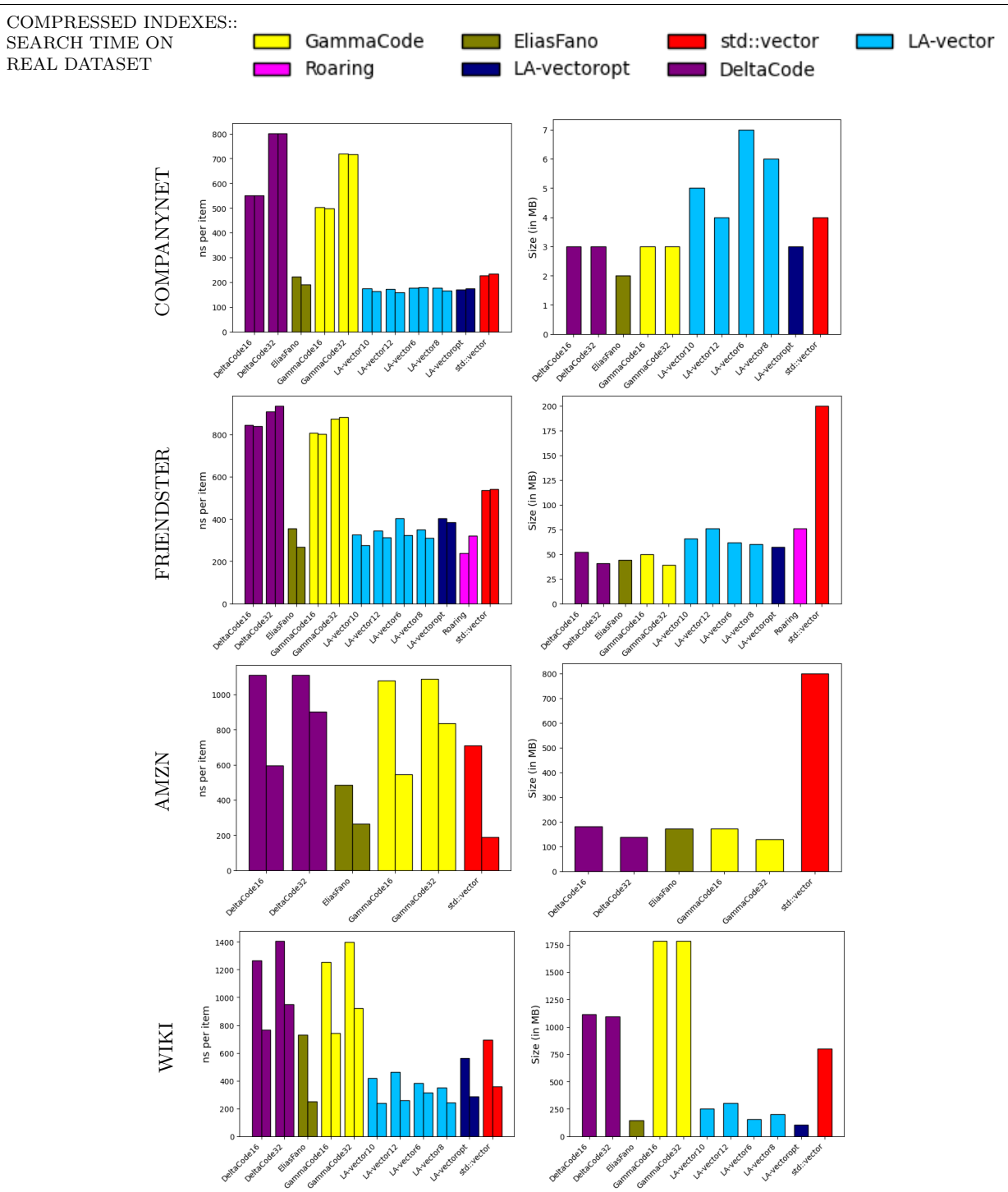
The performance of traditional and learned indexes on synthetic datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot shows two bars for each data structure. The left/right one shows the average time to search for an existing/missing item in the collection.

Figure 17: Average time for pointwise queries on traditional and learned indexes, built on synthetic datasets.



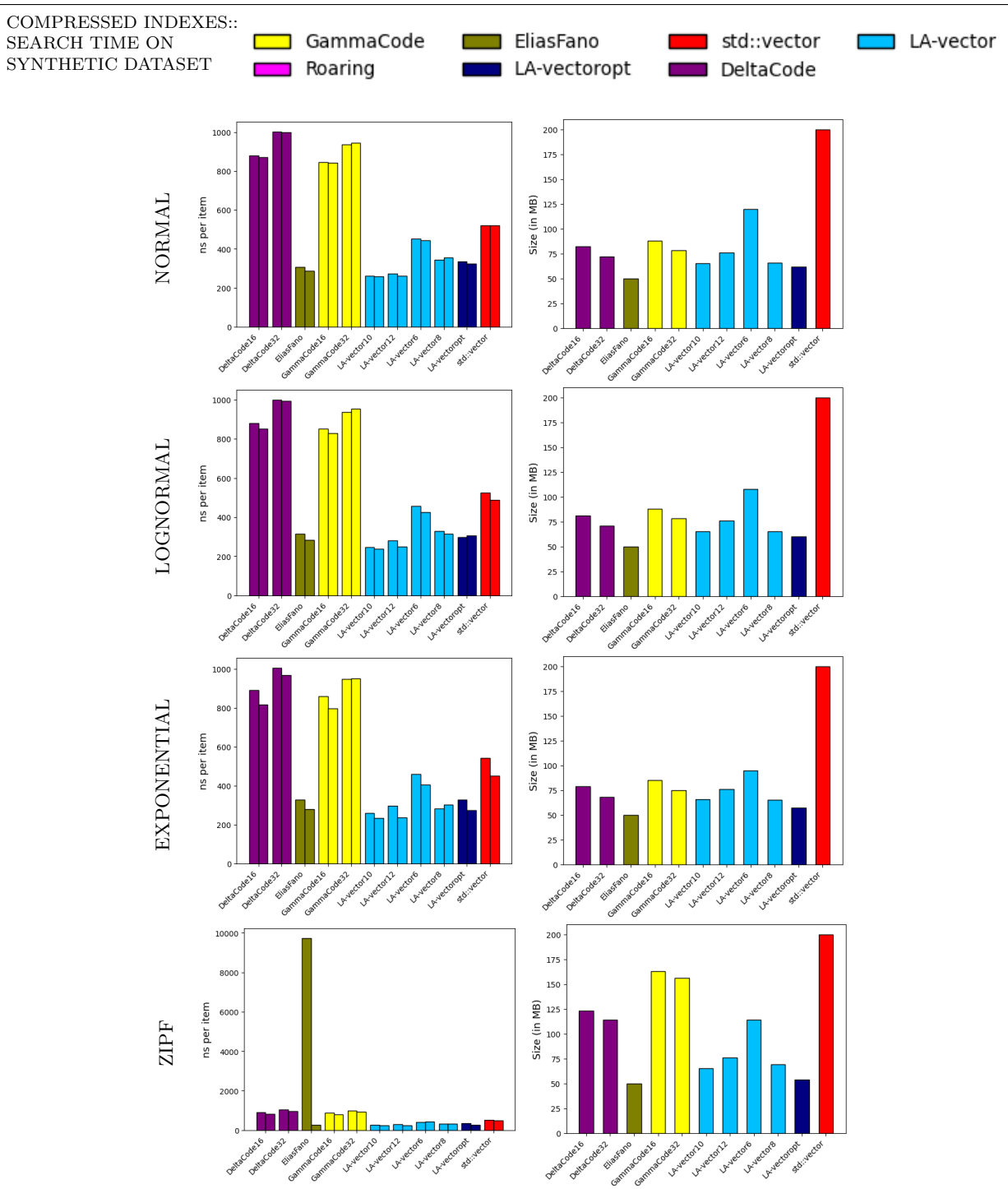
The performances of traditional and learned indexes on 64-bit datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot shows two bars for each data structure. The left/right one shows the average time to search for an existing/missing item in the collection.

Figure 18: Average time for pointwise queries on traditional and learned indexes, built on 64-bit datasets.



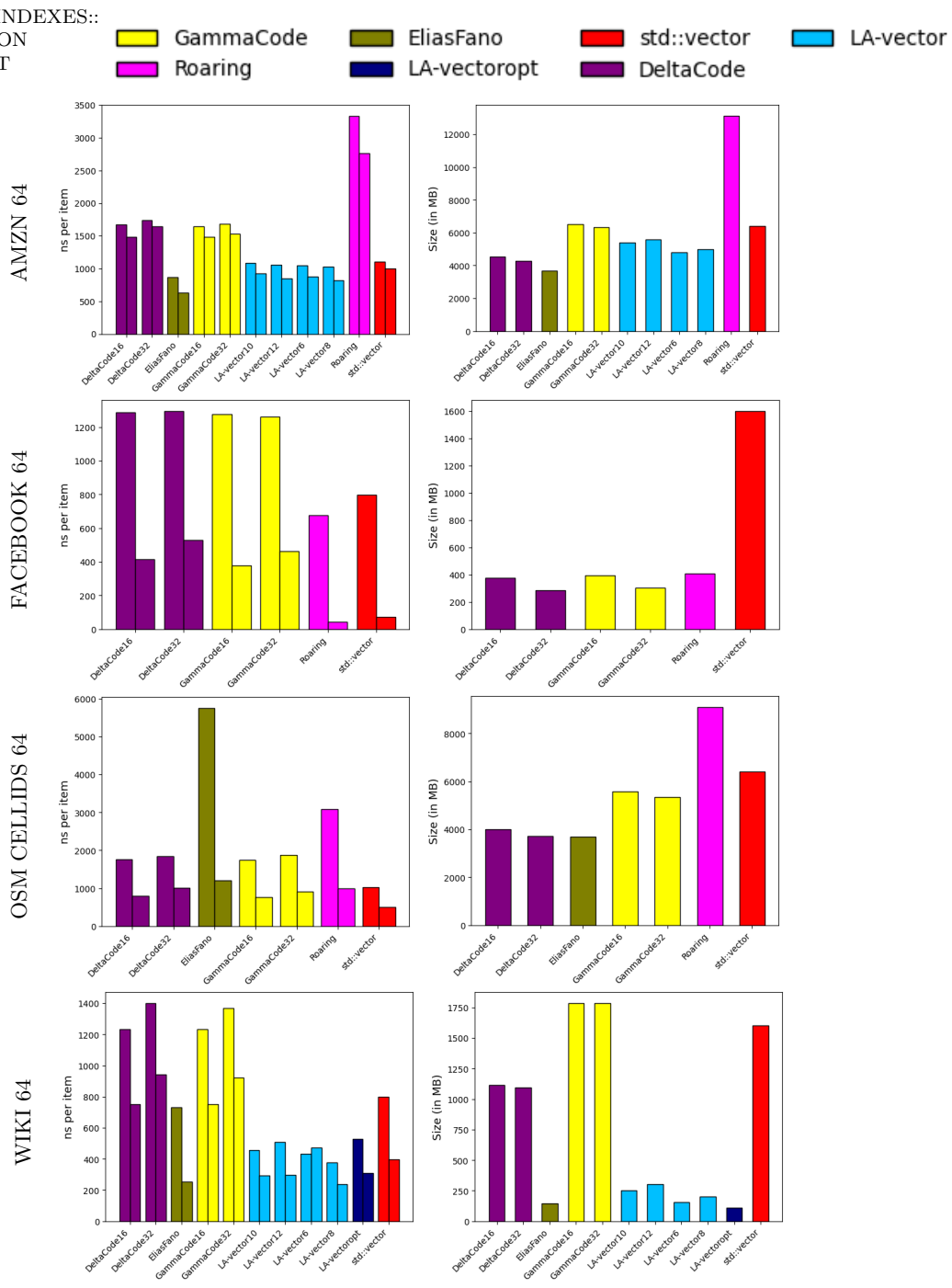
The performances of compressed indexes on real-world datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot shows two bars for each data structure. The left/right one shows the average time to search for an existing/missing item in the collection.

Figure 19: Average time for pointwise queries on compressed indexes, built on real-world datasets.



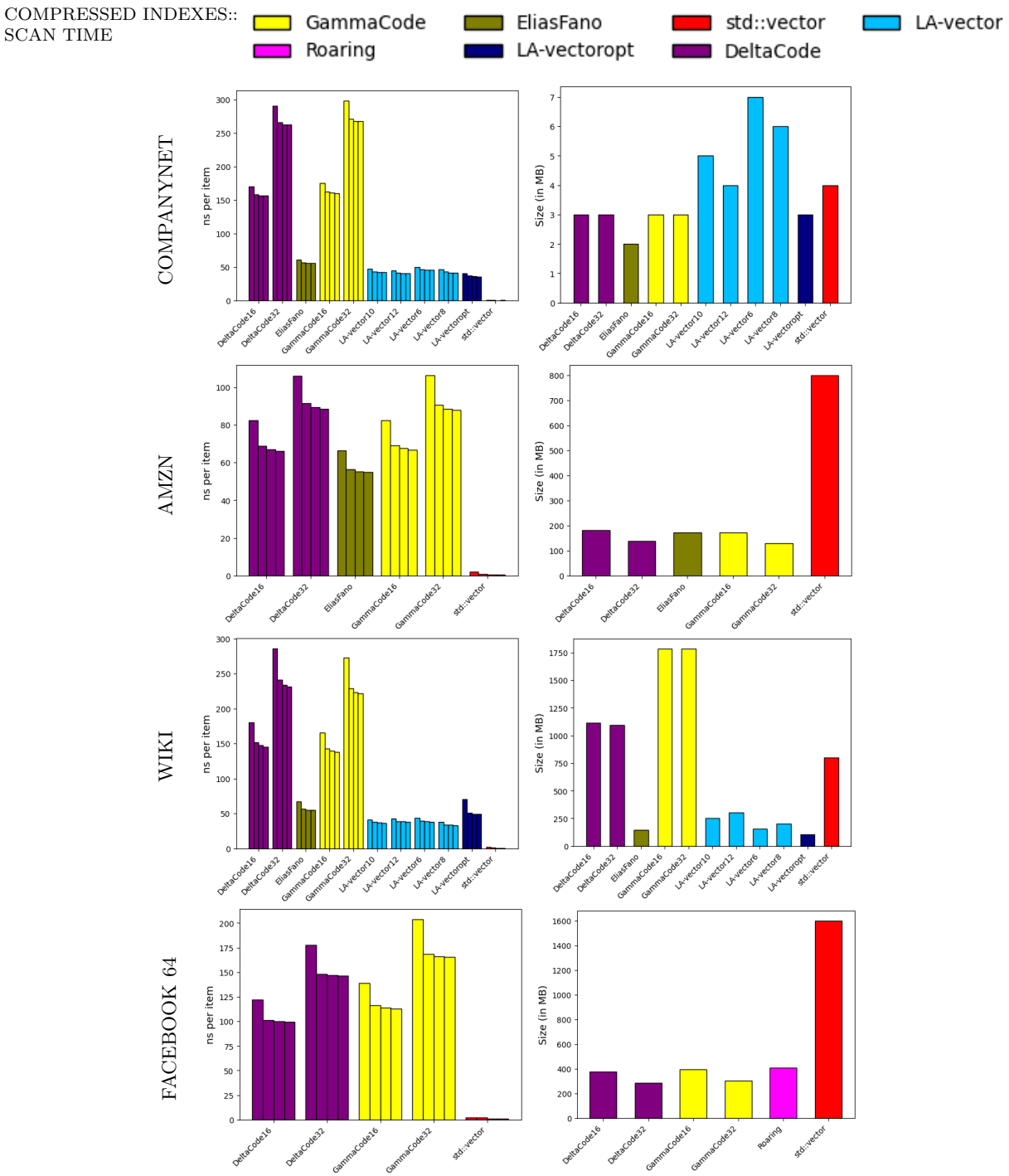
The performances of compressed indexes on synthetic datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot shows two bars for each data structure. The left/right one shows the average time to search for an existing/missing item in the collection.

Figure 20: Average time for pointwise queries on compressed indexes, built on synthetic datasets.



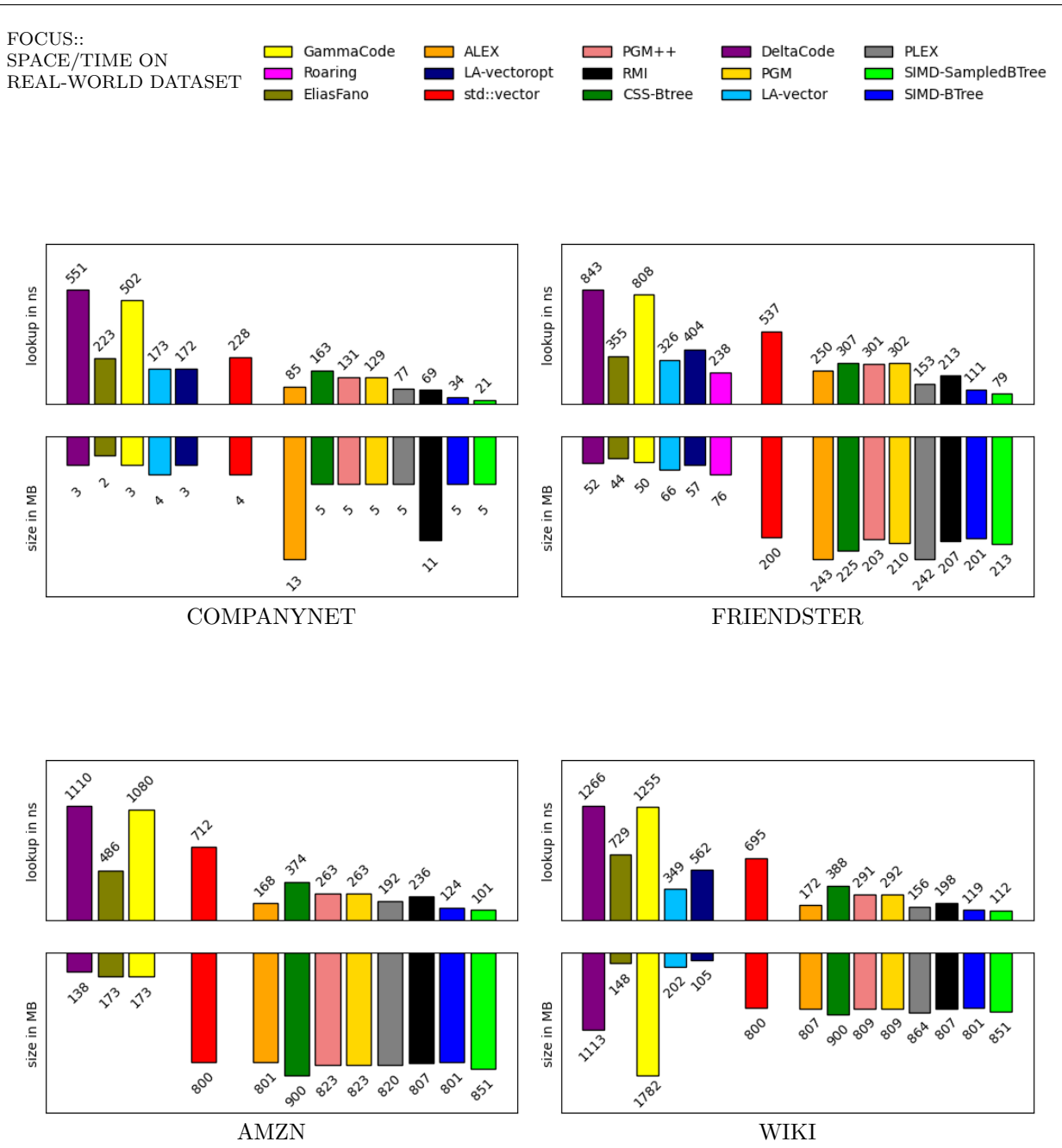
The performances of compressed indexes on 64-bit datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot shows two bars for each data structure. The left/right one shows the average time to search for an existing/missing item in the collection.

Figure 21: Average time for pointwise queries on compressed indexes, built on 64-bit datasets.



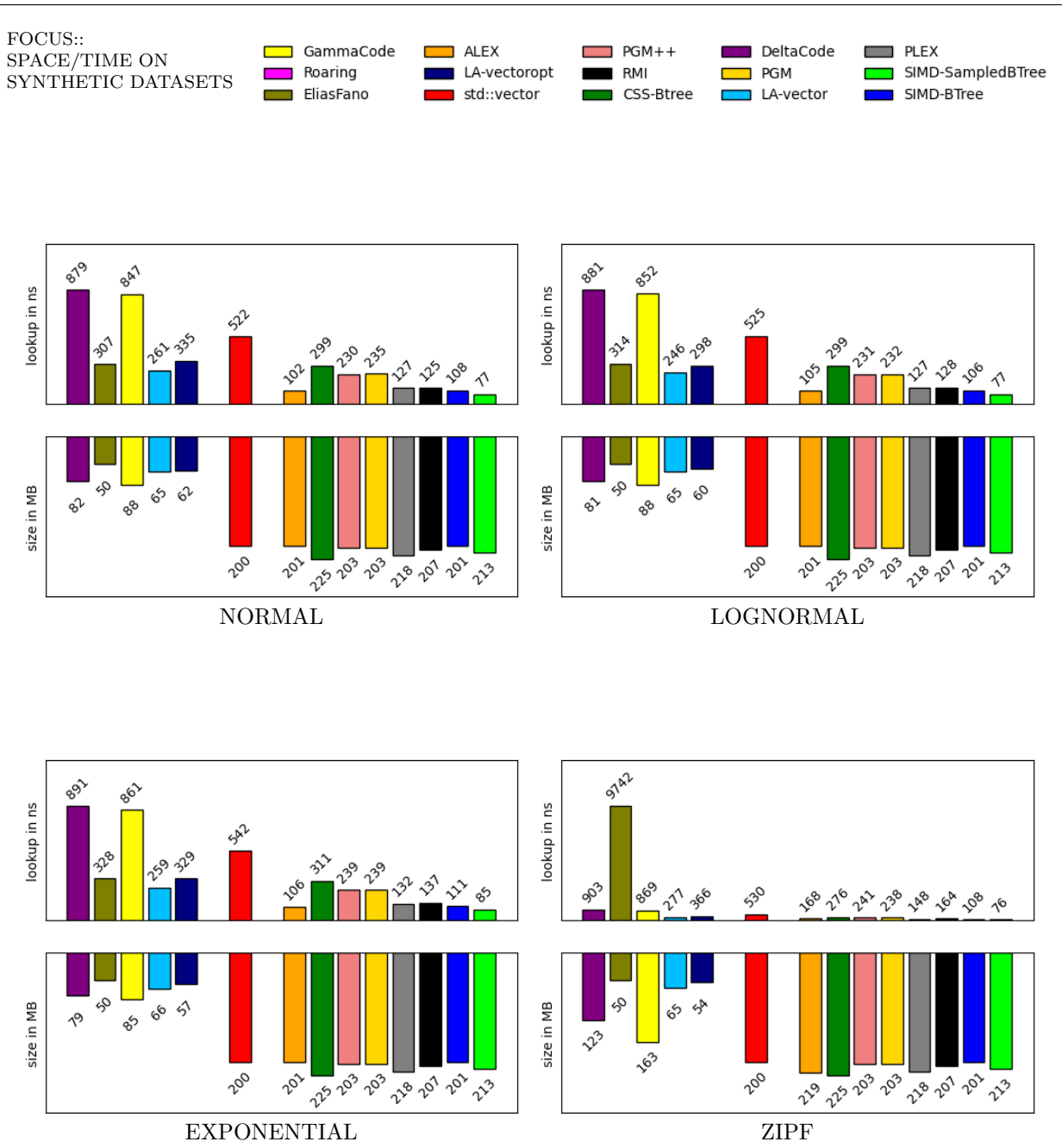
The plots above show the performance of compressed indexes in time and space relative to *range queries*, where starting points are randomly sampled, and the width of the scan is set to 10, 100, 1K, and 10K. The plot on the left shows the time (in ns) required for every interrogation, describing the average time required per access with $x = 10, 100, 1K, 10K$. The plot on the right shows the space occupied by each compressed index (in MB).

Figure 22: Average time (in ns) for range queries on compressed indexes, on 4 real-world datasets.



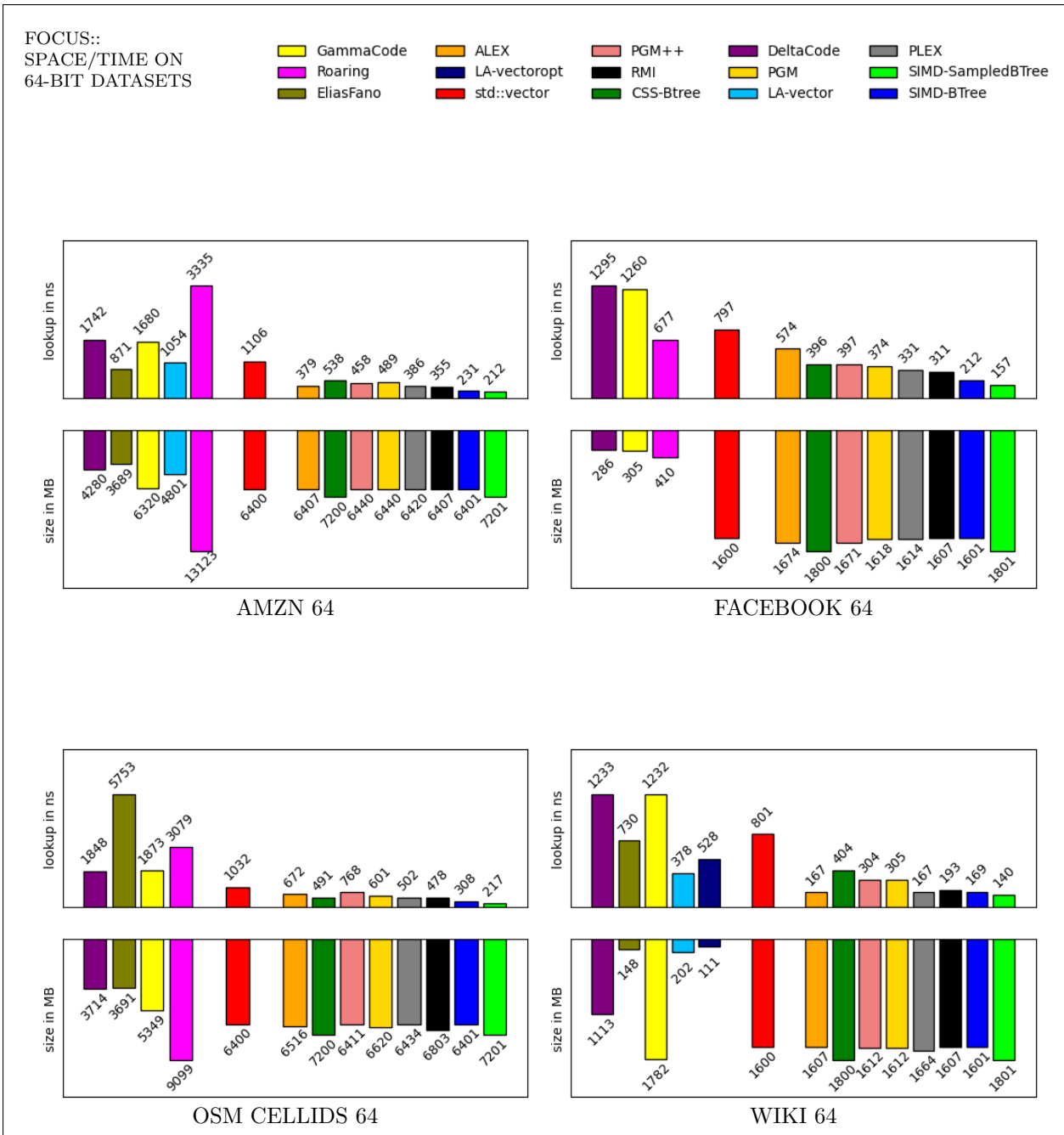
The figures above show the results corresponding to the space occupied and elapsed time for pointwise queries on real-world datasets on all tested indexes (traditional, learned, and compressed). For each dataset and for each index, the top part shows the average time (in ns) needed to make a query on existing items in the dataset, while the bottom part shows the required space in MB (where we added the space of the std::vector for traditional and learned indexes). The results show only the parameter configurations where each index performs best.

Figure 23: Recap space/time plots for pointwise queries on real-world datasets.



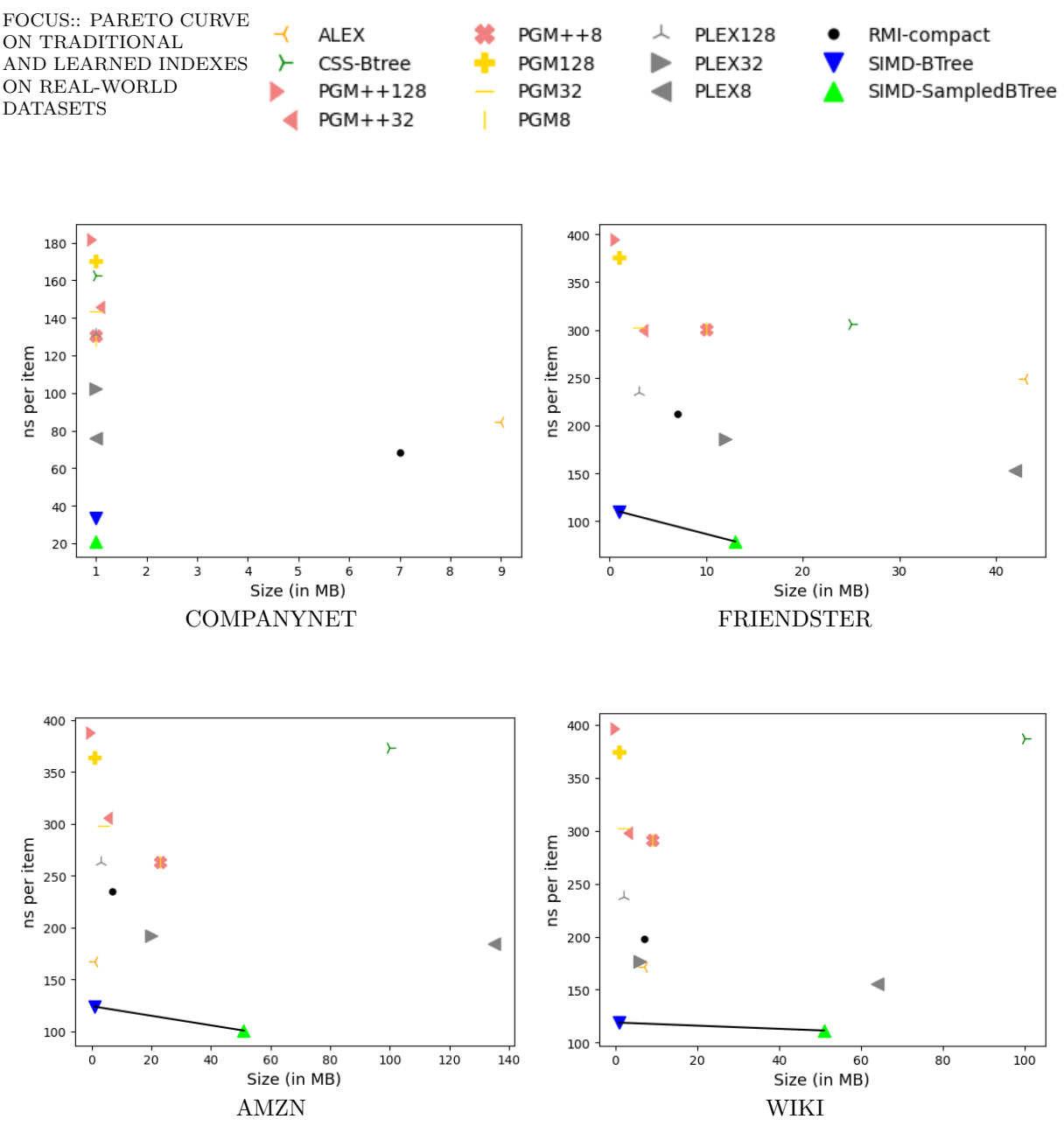
The figures above show the results corresponding to the space occupied and elapsed time for pointwise queries on synthetic datasets on all tested indexes (traditional, learned, and compressed). For each dataset and for each index, the top part shows the average time (in ns) needed to make a query on existing items in the dataset, while the bottom part shows the required space in MB (where we added the space of the std::vector for traditional and learned indexes). The results show only the parameter configurations where each index performs best.

Figure 24: Recap space/time plots for pointwise queries on synthetic datasets.



The figures above show the results corresponding to the space occupied and elapsed time for pointwise queries on 64-bit datasets on all tested indexes (traditional, learned, and compressed). For each dataset and each index, the top part shows the average time (in ns) needed to make a query on existing items in the dataset, while the bottom part shows the required space in MB (where we added the space of the std::vector for traditional and learned indexes). The results show only the parameter configurations where each index performs best.

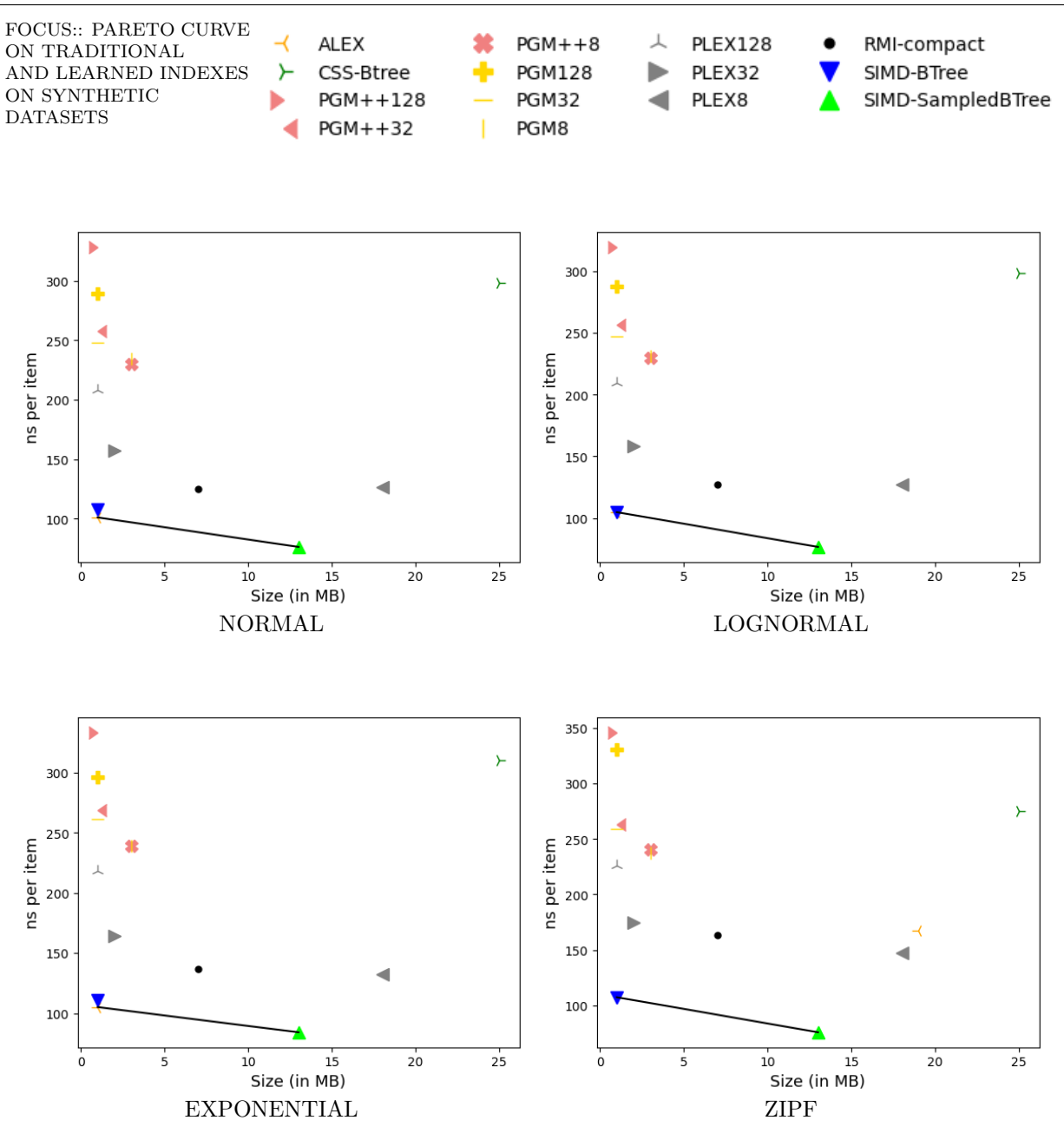
Figure 25: Recap space/time plots for pointwise queries on 64-bit datasets.



The plots recap the experimental results about occupied space/time needed for pointwise queries for traditional and learned indexes on real-world datasets. For these datasets, for each index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise query on existing items in the datasets.

Additionally, a black line shows the Pareto frontier for traditional/learned indexes. The indexes that sit on top of the Pareto frontier offer the best space-time trade-off. We avoided plotting "RMI-large" because of its excessive space occupancy (roughly 400 MB on each dataset). "RMI-large" was not one of the Pareto-optimal configurations.

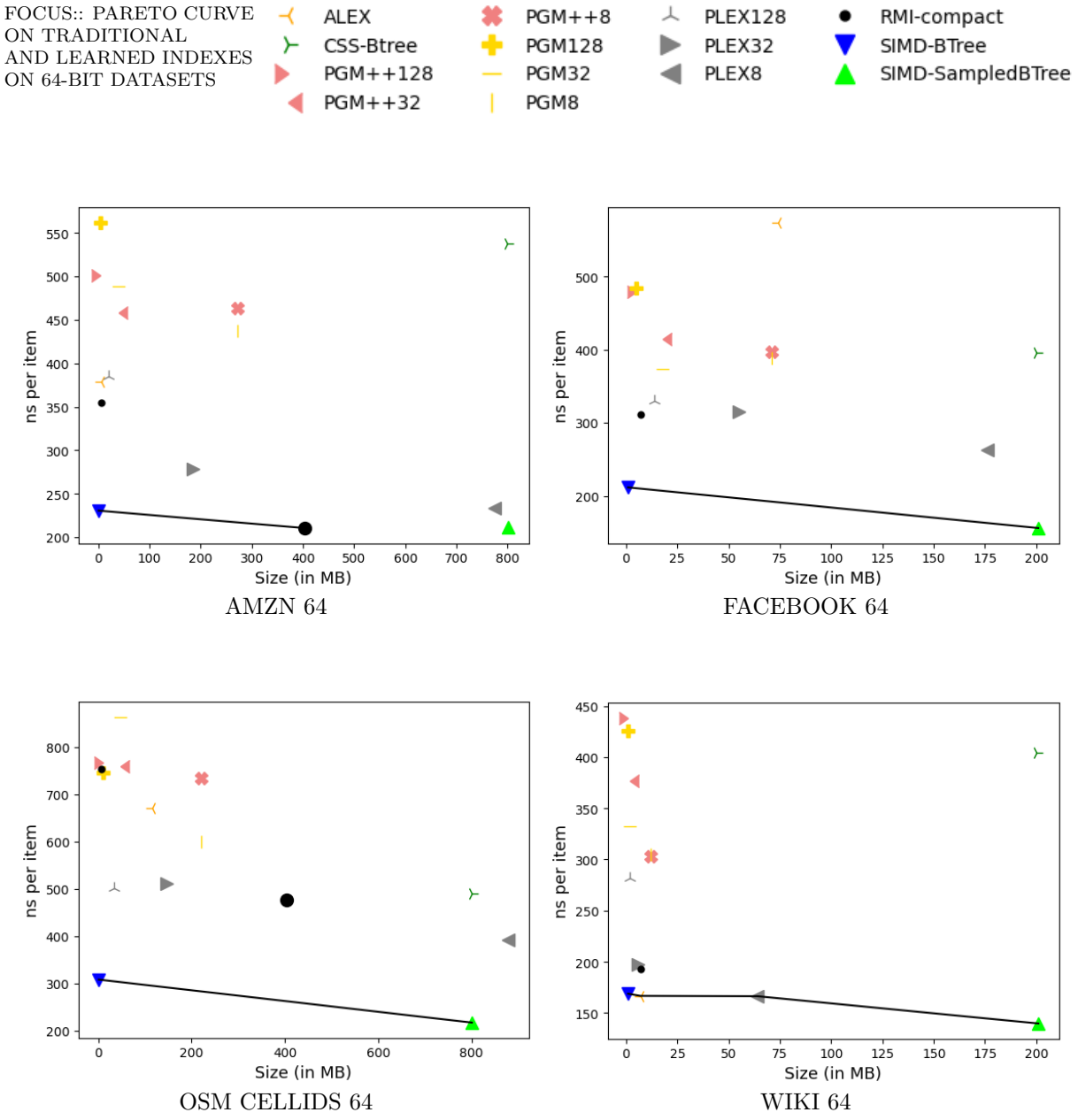
Figure 26: Pareto Frontier: Traditional and Learned Indexes on real-world datasets



The plots recap the experimental results about occupied space/time needed for pointwise queries for traditional and learned indexes on synthetic datasets. For these datasets, for each index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise query on existing items in the datasets.

Additionally, a black line shows the Pareto frontier for traditional/learned indexes. The indexes that sit on top of the Pareto frontier offer the best space-time trade-off. We avoided plotting "RMI-large" because of its excessive space occupancy (roughly 400 MB on each dataset). "RMI-large" was not one of the Pareto-optimal configurations.

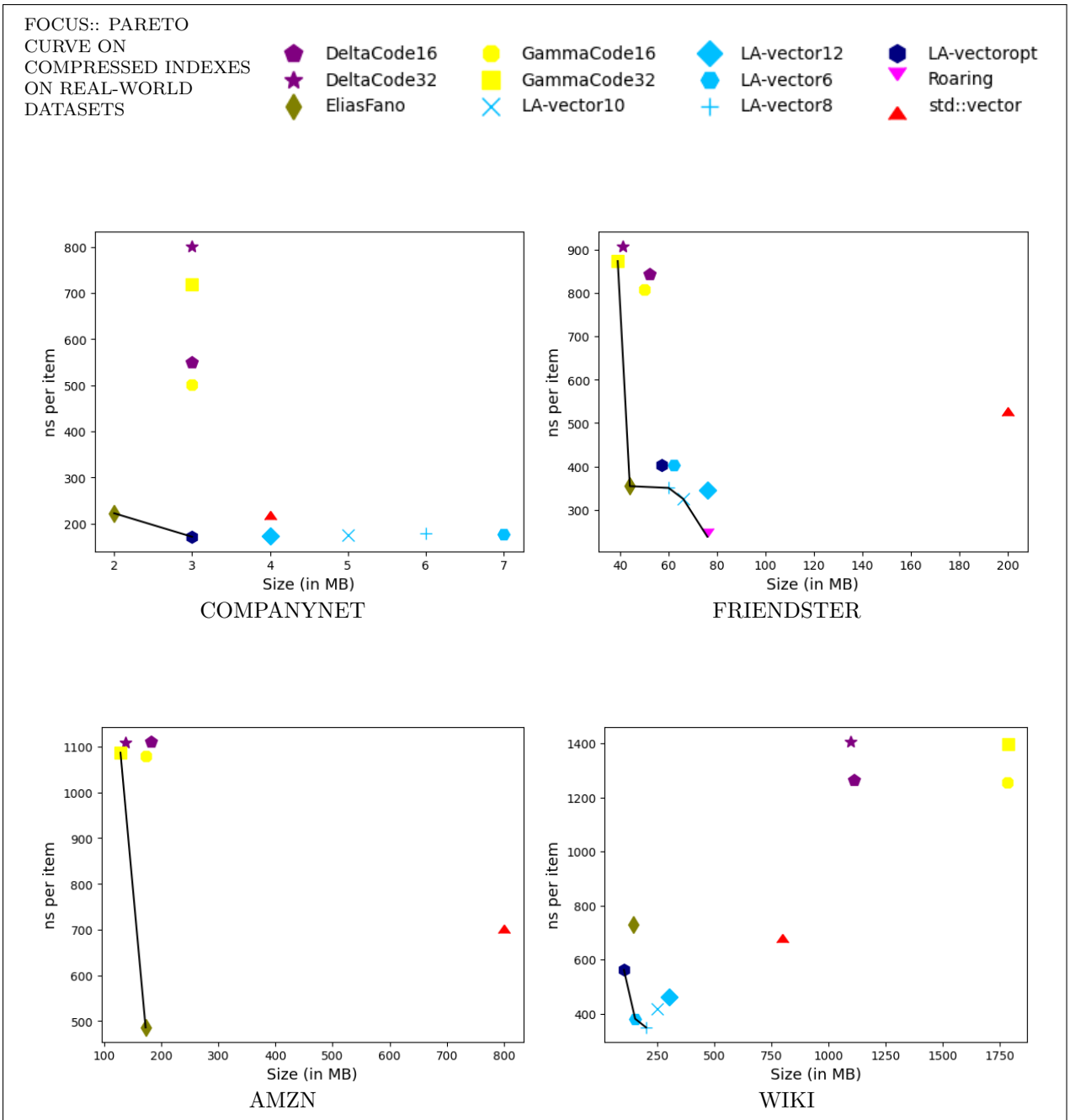
Figure 27: Pareto Frontier: Traditional and Learned Indexes on synthetic datasets



The plots recap the experimental results about occupied space/time needed for pointwise queries for traditional and learned indexes on 64-bit datasets. For these datasets, for each index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise query on existing items in the datasets.

Additionally, a black line shows the Pareto frontier for traditional/learned indexes. The indexes that sit on top of the Pareto frontier offer the best space-time trade-off. We avoided plotting "RMI-large" because of its excessive space occupancy (roughly 400 MB on each dataset). "RMI-large" was not one of the Pareto-optimal configurations.

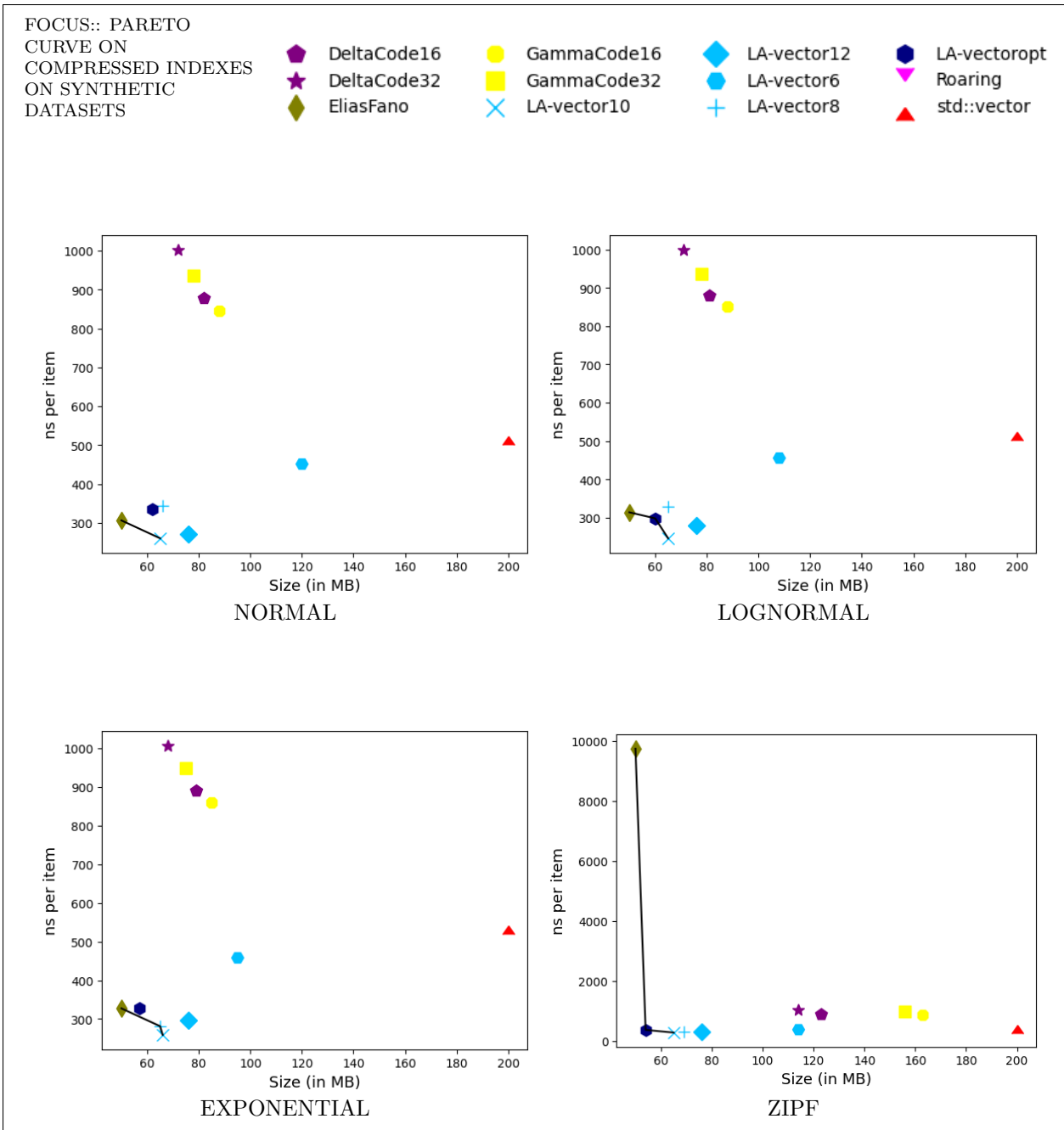
Figure 28: Pareto Frontier: Traditional and Learned Indexes on 64-bit datasets



The plots recap the experimental results about occupied space/time needed for pointwise queries for compressed indexes on real-world datasets. For these datasets, for each compressed index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise query on existing items in the datasets.

Additionally, a black line shows the Pareto frontier for traditional/learned indexes. The indexes that sit on top of the Pareto frontier offer the best space-time trade-off.

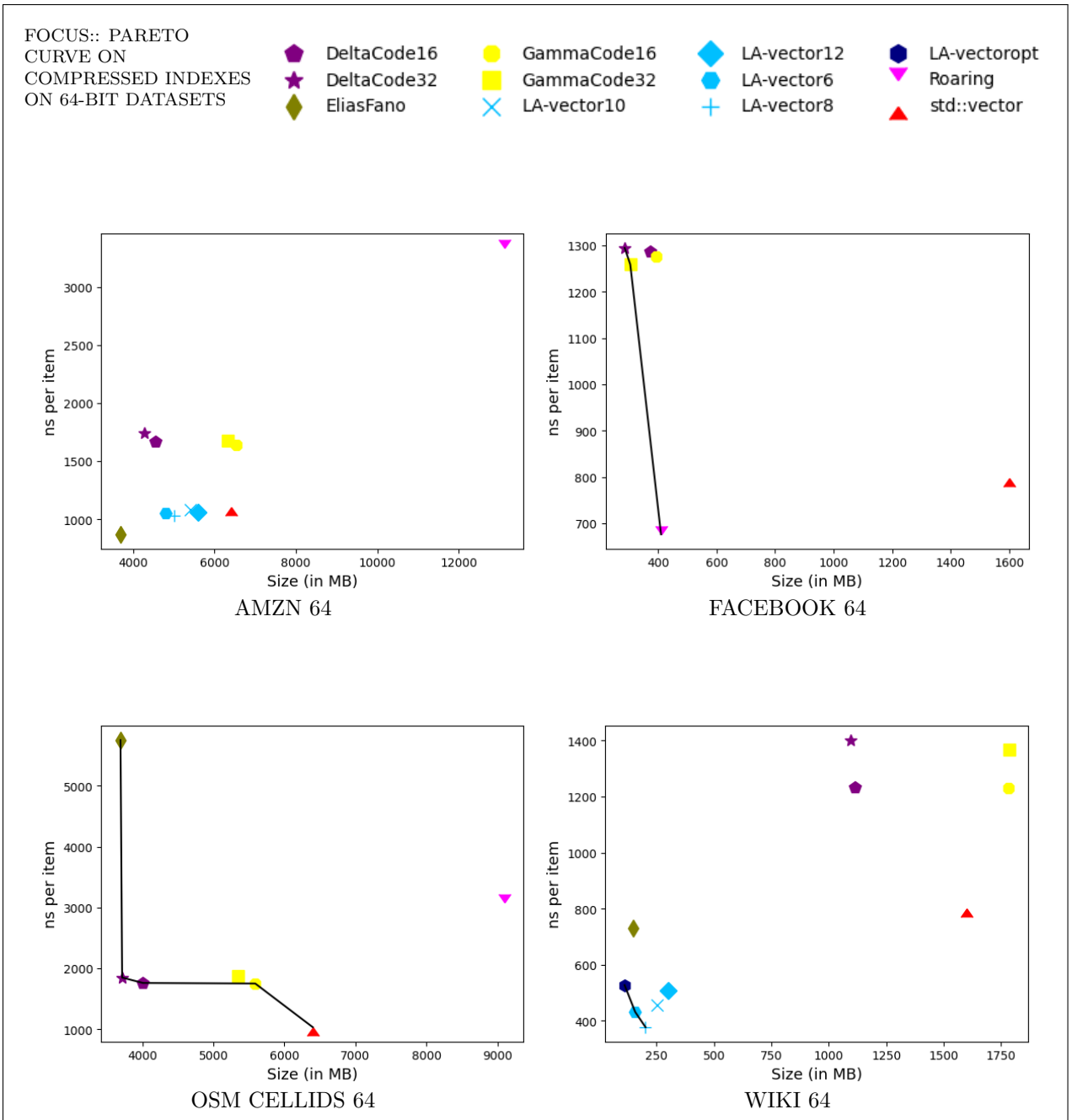
Figure 29: Pareto Frontier: Compressed Indexes on real-world datasets



The plots recap the experimental results about occupied space/time needed for pointwise queries for compressed indexes on synthetic datasets. For these datasets, for each compressed index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise query on existing items in the datasets.

Additionally, a black line shows the Pareto frontier for traditional/learned indexes. The indexes that sit on top of the Pareto frontier offer the best space-time trade-off.

Figure 30: Pareto Frontier: Compressed Indexes on synthetic datasets



The plots recap the experimental results about occupied space/time needed for pointwise queries for compressed indexes on 64-bit datasets. For these datasets, for each compressed index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise query on existing items in the datasets.

Additionally, a black line shows the Pareto frontier for traditional/learned indexes. The indexes that sit on top of the Pareto frontier offer the best space-time trade-off.

Figure 31: Pareto Frontier: Compressed Indexes on 64-bit datasets

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	84.795	75.2779	9	73.75703062862158
CSS-Btree	162.639	156.072	1	3.4730276092886925
DeltaCode16	550.163	550.164	3	28.494673501700163
DeltaCode32	801.402	801.772	3	31.99477568268776
EliasFano	222.173	190.123	2	34.575643856078386
GammaCode16	501.978	497.942	3	21.85149509459734
GammaCode32	718.739	716.487	3	22.436260525137186
LA-vector10	174.389	163.978	5	49.168580025434494
LA-vector12	172.844	158.693	4	31.820779386907816
LA-vector6	177.356	179.273	7	55.63622722402215
LA-vector8	177.742	165.176	6	50.25944449007511
LA-vectoropt	171.206	174.05	3	959.0857685543597
PGM++128	181.748	182.408	1	2.3462343961000443
PGM++32	145.778	148.903	1	2.3386308923363686
PGM++8	130.347	133.17	1	3.367249108850956
PGM128	170.391	176.688	1	2.3993615992367268
PGM32	143.277	144.125	1	2.3581955581903458
PGM8	128.272	129.927	1	3.406153805553913
PLEX128	131.528	141.461	1	18.869540933519602
PLEX32	102.084	97.9293	1	20.40441343560815
PLEX8	76.0505	80.3045	1	24.930240586400032
RMI-compact	68.2063	57.9312	7	3.148328699171543
RMI-large	87.104	73.6292	403	138.05404072627425
SIMD-BTree	33.1707	34.8978	1	4.20203460380435
SIMD-SampledBTree	20.9854	23.1505	1	2.844021935015917
std::vector	227.127	233.441	4	-

Table 1: Tabular data: companynet dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	171.216	130.978	7	12250.281422398983
CSS-Btree	387.456	209.897	100	1706.9255005568266
DeltaCode16	1265.27	766.646	1113	8585.237802937627
DeltaCode32	1406.5	951.687	1095	8918.436351884156
EliasFano	728.747	251.374	148	7772.2036364488295
GammaCode16	1254.4	743.391	1782	8558.242926280946
GammaCode32	1395.82	923.777	1785	8523.531216755511
LA-vector10	419.032	237.91	251	1924.8916687443852
LA-vector12	462.707	258.213	301	1744.617211818695
LA-vector6	380.864	315.315	154	2069.242195412517
LA-vector8	348.619	241.481	202	1795.6738444976509
LA-vectoropt	561.527	285.196	105	197673.87456940484
PGM++128	396.57	256.087	1	486.6906597279013
PGM++32	298.428	204.902	2	482.60454786941415
PGM++8	290.848	205.049	9	564.0171232633293
PGM128	374.152	246.121	1	492.8132425993681
PGM32	302.538	201.409	2	493.62632660195237
PGM8	291.528	201.788	9	569.1779868677258
PLEX128	237.739	174.58	2	3024.151705019176
PLEX32	176.581	121.453	6	3128.0779611319304
PLEX8	155.252	120.38	64	3749.1886020638044
RMI-compact	197.538	106.451	7	2.8465217910706997
RMI-large	135.004	101.825	403	235.64787851646543
SIMD-BTree	118.831	71.6056	1	1597.506396844983
SIMD-SampledBTree	111.367	53.0724	51	1569.045270420611
std::vector	694.065	360.534	800	-

Table 2: Tabular data: wiki uint32 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	249.282	228.425	43	3246.617103274911
CSS-Btree	306.611	287.862	25	202.8719955123961
DeltaCode16	842.925	838.148	52	1304.3092420324683
DeltaCode32	907.486	935.238	41	1437.6526718959212
EliasFano	354.424	268.447	44	1888.667493313551
GammaCode16	807.403	801.357	50	1035.195765644312
GammaCode32	873.273	882.188	39	1042.1883559785783
LA-vector10	325.142	276.805	66	526.3148916885257
LA-vector12	345.036	313.693	76	434.2422457411885
LA-vector6	402.512	323	62	811.9859673082829
LA-vector8	350.417	310.847	60	576.6228409484029
LA-vectoropt	403.264	384.947	57	52328.71983014047
PGM++128	394.567	375.317	1	131.2911598943174
PGM++32	300.058	288.891	3	157.84446522593498
PGM++8	300.258	288.922	10	204.41991137340665
PGM128	376.135	365.009	1	132.60455317795277
PGM32	302.368	286.235	3	159.1664945706725
PGM8	301.493	290.429	10	207.47915282845497
PLEX128	234.662	246.05	3	935.6957429088652
PLEX32	185.963	165.233	12	1099.8761787079275
PLEX8	152.585	158.389	42	1453.3371008001268
RMI-compact	212.397	177.803	7	1.707323081791401
RMI-large	126.462	116.152	403	210.64588781446218
Roaring	237.821	320.745	76	2254.525379184634
SIMD-BTree	110.103	104.483	1	292.07655750215054
SIMD-SampledBTree	78.882	74.924	13	169.29495614022017
std::vector	536.189	540.293	200	-

Table 3: Tabular data: friendster dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	105.054	85.9853	1	1793.1585018523037
CSS-Btree	310.346	252.282	25	205.26355598121881
DeltaCode16	890.872	816.098	79	1375.914961565286
DeltaCode32	1006.65	969.474	68	1508.2885845564306
EliasFano	327.316	280.85	50	1548.449839092791
GammaCode16	860.252	798.242	85	1065.6920091249049
GammaCode32	949.054	950.769	75	1072.1476834267378
LA-vector10	258.936	234.123	66	541.2897858768702
LA-vector12	297.423	236.388	76	419.2694471217692
LA-vector6	459.798	405.767	95	1195.4657504335046
LA-vector8	281.28	303.526	65	648.812757525593
LA-vectoropt	328.516	273.581	57	48586.33680455387
PGM++128	333.256	273.656	1	80.65461004152894
PGM++32	268.757	236.751	1	93.85824017226696
PGM++8	238.733	211.15	3	130.35861048847437
PGM128	296.382	260.838	1	81.67381696403027
PGM32	261.463	224.831	1	95.62891321256757
PGM8	238.67	207.413	3	132.73333692923188
PLEX128	218.257	196.585	1	831.1884633265436
PLEX32	164.447	136.248	2	958.1081283278763
PLEX8	131.953	121.509	18	1244.4443267770112
RMI-compact	136.908	110.583	7	2.8630591928958893
RMI-large	100.939	101.656	403	130.79720977693796
SIMD-BTree	110.86	85.3157	1	273.06970302015543
SIMD-SampledBTree	84.1393	61.7075	13	169.15717972442508
std::vector	541.996	450.289	200	-

Table 4: Tabular data: exponential dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	104.909	91.3408	1	1925.961231160909
CSS-Btree	298.479	280.769	25	218.5609022155404
DeltaCode16	880.698	851.485	81	1481.6991727799177
DeltaCode32	999.842	994.071	71	1628.5341411828995
EliasFano	313.658	283.585	50	1690.9992746077478
GammaCode16	851.016	828.575	88	1133.4734314121306
GammaCode32	937.174	953.315	78	1160.4485894553363
LA-vector10	245.619	237.983	65	549.7058939188719
LA-vector12	279.572	250.127	76	432.9594735987484
LA-vector6	456.651	425.821	108	1374.7535319067538
LA-vector8	329.223	314.825	65	673.0958395637572
LA-vectoropt	297.824	307.213	60	51735.804896149784
PGM++128	319.303	272.324	1	84.86448731273413
PGM++32	256.398	223.029	1	100.77933352440596
PGM++8	230.012	204.547	3	139.7454835474491
PGM128	287.646	253.085	1	86.89087992534041
PGM32	246.915	219.002	1	102.8373247012496
PGM8	231.244	202.007	3	139.11216026172042
PLEX128	209.419	209.191	1	881.0721554793417
PLEX32	158.246	145.083	2	1011.7294962517917
PLEX8	126.922	128.496	18	1326.587322447449
RMI-compact	127.217	118.769	7	3.2331787049770355
RMI-large	116.657	121.766	403	132.91828390210867
SIMD-BTree	105.188	104.163	1	307.0186988450587
SIMD-SampledBTree	76.7902	71.7349	13	182.32362996786833
std::vector	524.067	488.268	200	-

Table 5: Tabular data: lognormal dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	167.383	175.213	19	3206.527156382799
CSS-Btree	275.09	268.488	25	213.11991214752197
DeltaCode16	902.359	823.844	123	1464.7299736738205
DeltaCode32	1034.87	966.477	114	1581.4263638108969
EliasFano	9741.94	280.261	50	1588.2252238690853
GammaCode16	868.381	802.847	163	1189.699086919427
GammaCode32	980.971	928.791	156	1196.6758254915476
LA-vector10	276.811	230.765	65	530.0668471492826
LA-vector12	299.576	233.954	76	406.32175859063864
LA-vector6	399.53	431.715	114	1475.261174608022
LA-vector8	314.007	332.131	69	709.6805506385863
LA-vectoropt	365.824	276.092	54	48099.23371775076
PGM++128	345.919	321.539	1	84.51447850093246
PGM++32	262.665	246.796	1	100.50335852429271
PGM++8	240.177	224.297	3	136.39455512166023
PGM128	330.631	314.629	1	85.96834968775511
PGM32	258.713	240.903	1	102.39530261605978
PGM8	237.098	221.211	3	139.21683970838785
PLEX128	226.382	212.227	1	795.402083452791
PLEX32	174.259	145.882	2	903.677577804774
PLEX8	147.392	126.838	18	1169.3859842605889
RMI-compact	163.43	110.803	7	1.9203823059797287
RMI-large	110.573	102.847	403	163.96219404414296
SIMD-BTree	107.4	88.0679	1	283.4481427446008
SIMD-SampledBTree	75.8451	64.8493	13	189.14671139791608
std::vector	529.908	481.796	200	-

Table 6: Tabular data: zipf dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	101.038	89.5688	1	1566.5375479497015
CSS-Btree	298.307	293.062	25	254.6557548455894
DeltaCode16	878.739	872.093	82	1372.1612793393433
DeltaCode32	1002.53	999.058	72	1507.112545799464
EliasFano	306.291	287.017	50	1552.9780947603285
GammaCode16	846.473	843.143	88	1054.826890863478
GammaCode32	935.681	944.724	78	1078.2303439453244
LA-vector10	260.203	257.764	65	514.1205842606724
LA-vector12	271.374	260.617	76	399.65649181976914
LA-vector6	453.085	443.034	120	1404.7692891210318
LA-vector8	344.367	356.074	66	633.3029716275632
LA-vectoropt	334.535	324.737	62	48471.24777473509
PGM++128	328.339	323.115	1	85.10158443823457
PGM++32	258.105	254.79	1	100.47295140102506
PGM++8	229.672	234.455	3	136.7074745707214
PGM128	289.289	297.185	1	86.49016143754125
PGM32	248.307	244.356	1	99.07236052677035
PGM8	234.847	229.159	3	141.95491764694452
PLEX128	207.873	215.56	1	829.7714580781758
PLEX32	157.443	151.75	2	953.0407358892262
PLEX8	126.653	131.623	18	1254.7215035185218
RMI-compact	124.905	118.324	7	1.9787837751209736
RMI-large	117.204	120.689	403	200.49155429005623
SIMD-BTree	107.516	103.903	1	273.75347279012203
SIMD-SampledBTree	76.2583	77.1358	13	179.5007678680122
std::vector	521.889	521.671	200	-

Table 7: Tabular data: normal dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	167.491	65.8118	1	8640.326638147237
CSS-Btree	373.425	122.897	100	895.0018980540335
DeltaCode16	1111.35	594.898	182	5179.599394556135
DeltaCode32	1109.42	901.669	138	5678.040392138063
EliasFano	485.996	263.342	173	8624.733662419021
GammaCode16	1079.56	545.488	173	4141.609657555818
GammaCode32	1086.91	836.371	129	4184.847289696336
PGM++128	387.687	160.025	1	408.7858649902046
PGM++32	306.026	149.758	4	538.5268438607454
PGM++8	262.989	136.68	23	710.4559537954628
PGM128	363.67	145.096	1	413.0248161032796
PGM32	297.806	130.935	4	540.0404484011233
PGM8	262.699	124.676	23	718.4543122537434
PLEX128	263.166	108.248	3	3356.922280602157
PLEX32	191.716	102.956	20	3736.076870933175
PLEX8	184.065	125.158	135	4980.627958942206
RMI-compact	235.018	143.763	7	4.174442123621702
RMI-large	184.596	134.513	403	316.3726764731109
SIMD-BTree	123.756	53.5838	1	1019.2036591470242
SIMD-SampledBTree	100.765	41.9515	51	666.5759796276689
std::vector	711.094	188.601	800	-

Table 8: Tabular data: amzn uint32 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	378.669	375.659	7	51129.56800432876
CSS-Btree	537.161	473.147	800	13740.855899453163
DeltaCode16	1669.93	1486.91	4554	34080.375880375504
DeltaCode32	1741.05	1641.7	4280	34163.247584644705
EliasFano	870.018	633.128	3689	38514.73539825529
GammaCode16	1641.88	1480.54	6529	29730.070564337075
GammaCode32	1679.7	1529.27	6320	29658.555390592664
LA-vector10	1083.72	930.558	5401	88643.91160393134
LA-vector12	1062.75	852.285	5601	99877.44658198209
LA-vector6	1053.73	879.114	4801	87544.65185552835
LA-vector8	1033.01	825.049	5001	88549.01628801599
PGM++128	501.538	528.537	5	2045.27162918821
PGM++32	457.759	468.919	40	2536.897181160748
PGM++8	463.501	449.182	273	3789.1560167074203
PGM128	561.801	490.928	5	2093.4837545268238
PGM32	488.42	431.021	40	2606.6456430591647
PGM8	437.634	429.747	273	4060.1327461190517
PLEX128	385.164	337.635	20	15909.060241281986
PLEX32	278.458	276.138	186	17986.660381499674
PLEX8	233.454	229.739	775	23171.494773123413
RMI-compact	354.264	297.817	7	2.939328085631132
RMI-large	210.585	193.132	403	193.0703278630972
Roaring	3334.82	2763.85	13123	240788.84463775903
SIMD-BTree	230.589	213.628	1	13592.78650265187
SIMD-SampledBTree	211.211	198.361	801	13623.581824917346
std::vector	1105.49	1005.29	6400	-

Table 9: Tabular data: amzn uint64 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	671.084	237.645	116	69691.36697929354
CSS-Btree	490.232	234.792	800	6953.189545404165
DeltaCode16	1758.77	794.365	4007	29418.319696933035
DeltaCode32	1847.87	1004.56	3714	29451.800709217783
EliasFano	5752.57	1206.97	3691	40745.86051572114
GammaCode16	1749.51	771.32	5589	26382.099382206794
GammaCode32	1872.32	918.599	5349	26258.016065694388
PGM++128	767.681	361.784	11	2465.7752173021436
PGM++32	759.417	310.022	48	2747.436973173171
PGM++8	733.479	302.344	220	3698.034436069429
PGM128	745.425	323.391	11	2458.1805650144815
PGM32	863.109	338.437	48	2775.2761832438405
PGM8	600.297	324.233	220	3746.428289171308
PLEX128	501.306	216.359	34	18645.951402187347
PLEX32	510.674	175.989	147	20487.78000697494
PLEX8	390.956	160.757	879	26167.933154292405
RMI-compact	754.173	131.459	7	2.3391788825392723
RMI-large	477.233	107.309	403	194.9591820128262
Roaring	3078.13	984.998	9099	187145.52908269686
SIMD-BTree	307.941	148.401	1	8230.164286028594
SIMD-SampledBTree	216.965	109.716	801	6987.790261860937
std::vector	1031.15	497.749	6400	-

Table 10: Tabular data: OSM cellids dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	166.736	146.297	7	13391.475207544865
CSS-Btree	403.955	236.624	200	3081.3959578052163
DeltaCode16	1232.16	752.528	1113	9473.718196246773
DeltaCode32	1401.09	941.488	1095	9415.486107673496
EliasFano	729.419	255.153	148	8688.635134417564
GammaCode16	1231.34	752.246	1782	9503.44590730965
GammaCode32	1366.65	921.002	1785	9399.666076339781
LA-vector10	455.316	294.902	251	3677.0167400129144
LA-vector12	506.993	296.99	301	3804.4929507188504
LA-vector6	431.688	470.686	157	3600.5042964592576
LA-vector8	377.027	237.212	202	3514.792509283871
LA-vectoropt	527.244	309.344	111	279102.5785423815
PGM++128	438.115	282.648	1	563.2405459880829
PGM++32	376.922	227.561	2	559.2115439474583
PGM++8	303.329	232.349	12	645.5309600569308
PGM128	425.689	275.343	1	583.743760921061
PGM32	332.312	227.73	2	575.504154805094
PGM8	304.436	218.545	12	674.3493216112256
PLEX128	281.411	195.393	2	3419.378320034593
PLEX32	197.446	143.372	6	3555.534276366234
PLEX8	166.412	123.024	64	4248.385151289403
RMI-compact	192.971	111.758	7	3.774173930287361
RMI-large	140.415	106.22	403	290.66189592704177
SIMD-BTree	168.845	96.0625	1	2983.481775876134
SIMD-SampledBTree	139.777	83.8916	201	3248.1671703048046
std::vector	800.183	396.749	1600	-

Table 11: Tabular data: wiki uint64 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	573.6	14.5306	74	18045.232778880745
CSS-Btree	395.47	70.4056	200	1310.8691022731364
DeltaCode16	1287.61	414.694	374	6417.9105745628485
DeltaCode32	1294.78	527.001	286	6509.404008742422
GammaCode16	1275.4	377.475	393	5320.555119868368
GammaCode32	1259.13	461.428	305	5343.3144599199295
PGM++128	479.12	95.6022	5	634.2772550880909
PGM++32	414.727	89.9523	18	730.3224395960569
PGM++8	396.81	113.925	71	1003.5413072444499
PGM128	484.534	96.599	5	653.158899396658
PGM32	373.327	94.9386	18	753.2375046052039
PGM8	388.017	101.629	71	1023.9377717487514
PLEX128	330.364	61.1977	14	4366.7933952994645
PLEX32	315.18	49.0181	55	4848.923907708376
PLEX8	262.922	52.3193	176	6190.323376934975
RMI-compact	310.753	37.2934	7	2.3477911949157715
RMI-large	213.143	37.4332	403	207.78175862506032
Roaring	676.09	44.9812	410	22295.894460659474
SIMD-BTree	211.628	50.3897	1	1318.8758626580238
SIMD-SampledBTree	156.053	33.8489	201	1299.4393265806139
std::vector	796.749	72.0668	1600	-

Table 12: Tabular data: FB uint64 dataset

Compressed Index	Scan 10	Scan 100	Scan 1K	Scan 10K
DeltaCode16	169.902	158.382	156.902	156.262
DeltaCode32	290.359	266.085	262.788	262.641
EliasFano	60.6795	56.5687	56.0174	55.8601
GammaCode16	174.914	162.492	160.746	160.167
GammaCode32	298.385	271.448	268.043	267.507
LA-vector10	47.289	43.3315	42.4952	42.3297
LA-vector12	45.0734	41.4511	40.76	40.6897
LA-vector6	49.6115	46.3757	45.3586	45.2125
LA-vector8	46.0287	42.6529	41.6661	41.5467
LA-vectoropt	40.5808	36.8136	35.9605	35.7708
std::vector	0.562015	0.220738	0.175476	0.251958

Table 13: Tabular data: SCAN experiments on the companynet dataset (times are expressed in ns)

Compressed Index	Scan 10	Scan 100	Scan 1K	Scan 10K
DeltaCode16	180.626	152.231	147.45	145.791
DeltaCode32	286.332	241.294	233.723	231.971
EliasFano	67.0721	56.6032	55.4092	55.0058
GammaCode16	165.895	143.288	139.686	137.795
GammaCode32	272.873	229.1	223.36	221.512
LA-vector10	40.9013	38.0294	37.3074	36.7726
LA-vector12	42.8927	39.0475	39.1278	38.3544
LA-vector6	43.78	39.3341	38.73	38.2743
LA-vector8	38.0936	34.117	34.0408	33.5231
LA-vectoropt	70.3335	51.1309	49.5432	49.0797
std::vector	2.12109	1.38943	0.51784	0.472924

Table 14: Tabular data: SCAN experiments on the wiki uint32 dataset (times are expressed in ns)

Compressed Index	Scan 10	Scan 100	Scan 1K	Scan 10K
DeltaCode16	82.4027	68.7572	67.0358	66.135
DeltaCode32	105.84	91.3301	89.1847	88.4595
EliasFano	66.3994	56.3723	55.3097	54.8652
GammaCode16	82.4171	68.9434	67.5749	66.7945
GammaCode32	106.273	90.424	88.482	87.7333
std::vector	2.05005	0.72798	0.505714	0.435934

Table 15: Tabular data: SCAN experiments on the amzn uint32 dataset (times are expressed in ns)

Compressed Index	Scan 10	Scan 100	Scan 1K	Scan 10K
DeltaCode16	122.292	100.978	100.201	99.5831
DeltaCode32	177.565	147.963	147.04	146.48
GammaCode16	138.96	116.163	113.737	112.854
GammaCode32	203.884	168.636	165.93	165.224
std::vector	2.35548	2.16368	0.963471	0.925722

Table 16: Tabular data: SCAN experiments on the FB uint64 dataset (times are expressed in ns)

Error Report

LA-vectoropt - fb_200M_uint64 - existing: First correction too large
LA-vector6 - fb_200M_uint64 - existing: Bit fields' sizes are not large enough
LA-vector8 - fb_200M_uint64 - existing: Bit fields' sizes are not large enough
LA-vector10 - fb_200M_uint64 - existing: Bit fields' sizes are not large enough
LA-vector12 - fb_200M_uint64 - existing: Bit fields' sizes are not large enough
LA-vectoropt - books_800M_uint64 - existing: First correction too large
LA-vectoropt - osm_cellids_800M_uint64 - existing: First correction too large
LA-vector6 - osm_cellids_800M_uint64 - existing: Segment correction too large
LA-vector8 - osm_cellids_800M_uint64 - existing: Segment correction too large
LA-vector10 - osm_cellids_800M_uint64 - existing: Segment correction too large
LA-vector12 - osm_cellids_800M_uint64 - existing: Segment correction too large
LA-vectoropt - books_200M_uint32 - existing: Bit fields' sizes are not large enough
LA-vector6 - books_200M_uint32 - existing: Bit fields' sizes are not large enough
LA-vector8 - books_200M_uint32 - existing: Bit fields' sizes are not large enough
LA-vector10 - books_200M_uint32 - existing: Bit fields' sizes are not large enough
LA-vector12 - books_200M_uint32 - existing: Bit fields' sizes are not large enough
LA-vectoropt - fb_200M_uint64 - missing: First correction too large
LA-vector6 - fb_200M_uint64 - missing: Bit fields' sizes are not large enough
LA-vector8 - fb_200M_uint64 - missing: Bit fields' sizes are not large enough
LA-vector10 - fb_200M_uint64 - missing: Bit fields' sizes are not large enough
LA-vector12 - fb_200M_uint64 - missing: Bit fields' sizes are not large enough
LA-vectoropt - books_800M_uint64 - missing: First correction too large
LA-vectoropt - osm_cellids_800M_uint64 - missing: First correction too large
LA-vector6 - osm_cellids_800M_uint64 - missing: Segment correction too large
LA-vector8 - osm_cellids_800M_uint64 - missing: Segment correction too large
LA-vector10 - osm_cellids_800M_uint64 - missing: Segment correction too large
LA-vector12 - osm_cellids_800M_uint64 - missing: Segment correction too large
LA-vectoropt - books_200M_uint32 - missing: Bit fields' sizes are not large enough
LA-vector6 - books_200M_uint32 - missing: Bit fields' sizes are not large enough
LA-vector8 - books_200M_uint32 - missing: Bit fields' sizes are not large enough
LA-vector10 - books_200M_uint32 - missing: Bit fields' sizes are not large enough
LA-vector12 - books_200M_uint32 - missing: Bit fields' sizes are not large enough
LA-vectoropt - fb_200M_uint64 - buildtime: First correction too large
LA-vector6 - fb_200M_uint64 - buildtime: Bit fields' sizes are not large enough
LA-vector8 - fb_200M_uint64 - buildtime: Bit fields' sizes are not large enough
LA-vector10 - fb_200M_uint64 - buildtime: Bit fields' sizes are not large enough
LA-vector12 - fb_200M_uint64 - buildtime: Bit fields' sizes are not large enough
LA-vectoropt - books_800M_uint64 - buildtime: First correction too large
LA-vectoropt - osm_cellids_800M_uint64 - buildtime: First correction too large
LA-vector6 - osm_cellids_800M_uint64 - buildtime: Segment correction too large
LA-vector8 - osm_cellids_800M_uint64 - buildtime: Segment correction too large
LA-vector10 - osm_cellids_800M_uint64 - buildtime: Segment correction too large
LA-vector12 - osm_cellids_800M_uint64 - buildtime: Segment correction too large
LA-vectoropt - books_200M_uint32 - buildtime: Bit fields' sizes are not large enough
LA-vector6 - books_200M_uint32 - buildtime: Bit fields' sizes are not large enough
LA-vector8 - books_200M_uint32 - buildtime: Bit fields' sizes are not large enough
LA-vector10 - books_200M_uint32 - buildtime: Bit fields' sizes are not large enough
LA-vector12 - books_200M_uint32 - buildtime: Bit fields' sizes are not large enough
LA-vectoropt - fb_200M_uint64 - scan: First correction too large
LA-vector6 - fb_200M_uint64 - scan: Bit fields' sizes are not large enough

LA-vector8 - fb_200M_uint64 - scan: Bit fields' sizes are not large enough
LA-vector10 - fb_200M_uint64 - scan: Bit fields' sizes are not large enough
LA-vector12 - fb_200M_uint64 - scan: Bit fields' sizes are not large enough
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LA-vectoropt - books_200M_uint32 - scan: Bit fields' sizes are not large enough
LA-vector6 - books_200M_uint32 - scan: Bit fields' sizes are not large enough
LA-vector8 - books_200M_uint32 - scan: Bit fields' sizes are not large enough
LA-vector10 - books_200M_uint32 - scan: Bit fields' sizes are not large enough
LA-vector12 - books_200M_uint32 - scan: Bit fields' sizes are not large enough