REAL-WORLD
DATASETS DISTRIBUTION

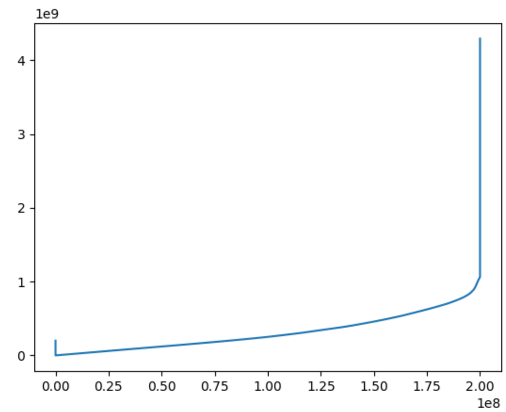


Figure 1: Amzn uint32

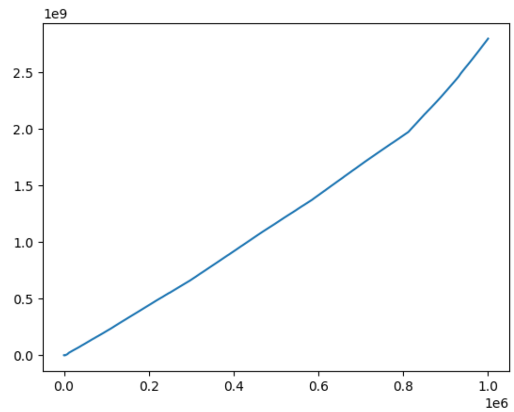


Figure 2: CompanyNet

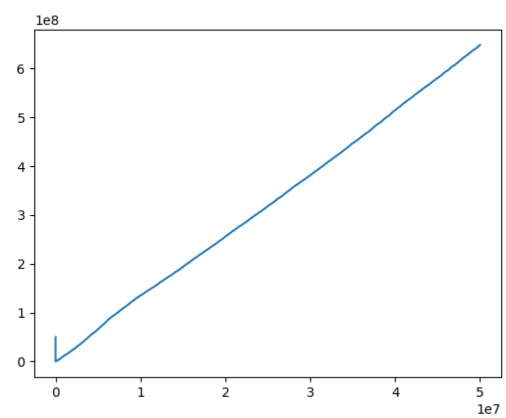


Figure 3: Friendster

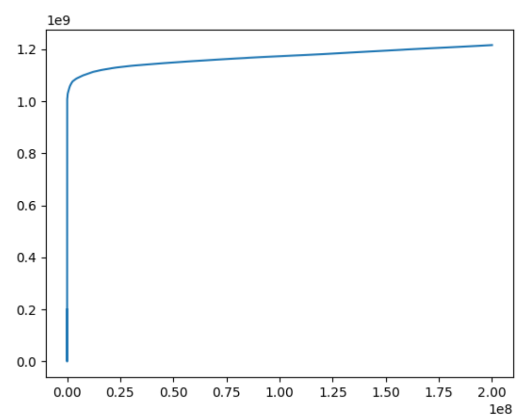


Figure 4: Wiki uint32

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

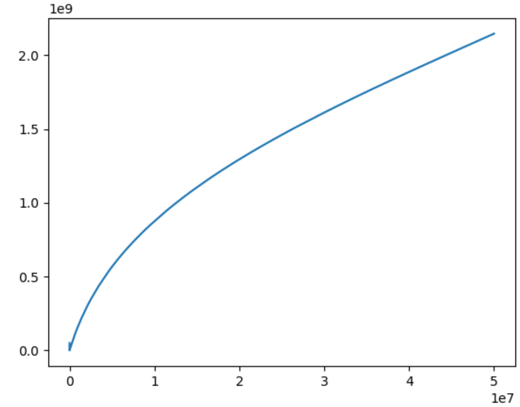


Figure 5: Normal

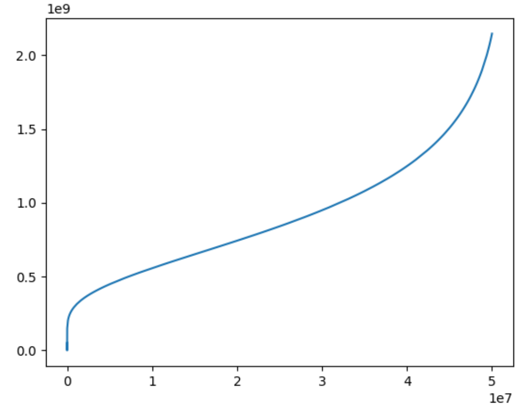


Figure 6: Lognormal

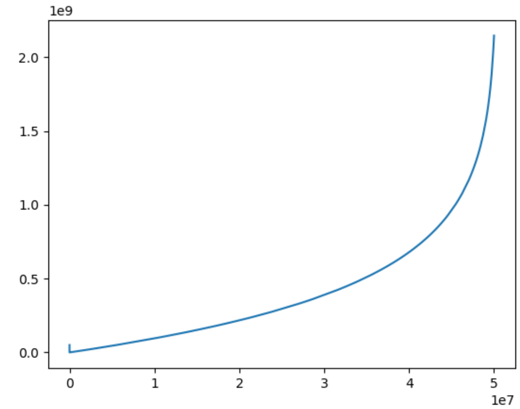


Figure 7: Exponential

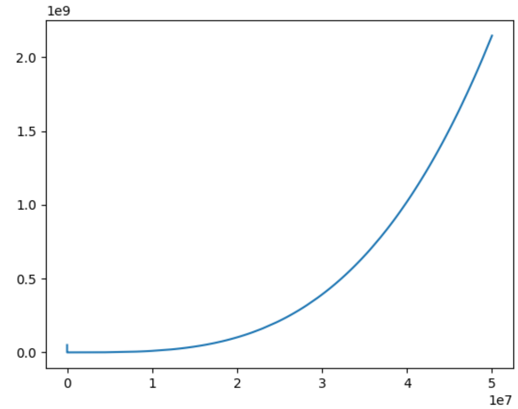


Figure 8: Zipf

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

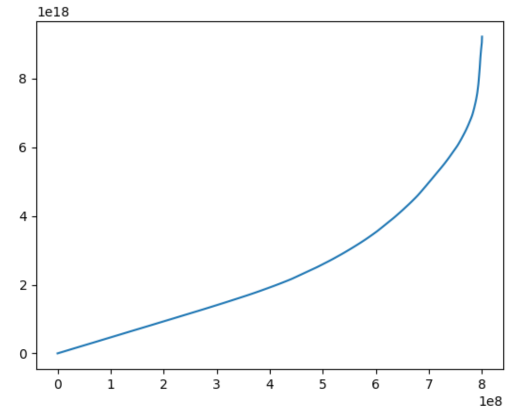


Figure 9: Amzn uint64

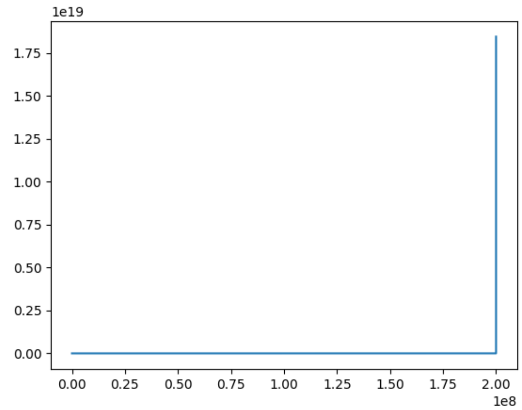


Figure 10: Facebook uint64

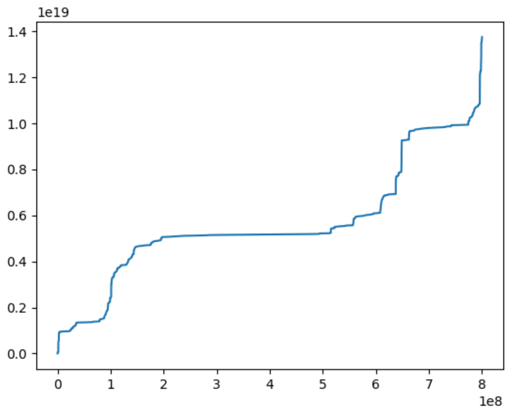


Figure 11: OSM Cellids uint64

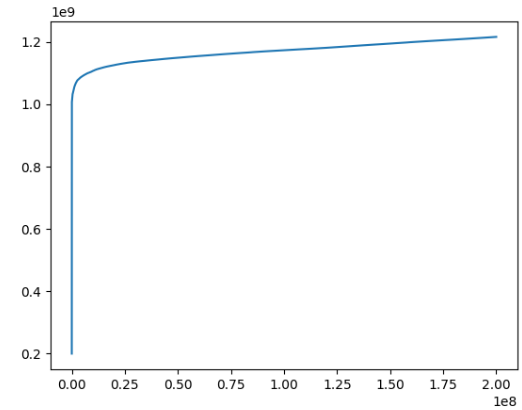
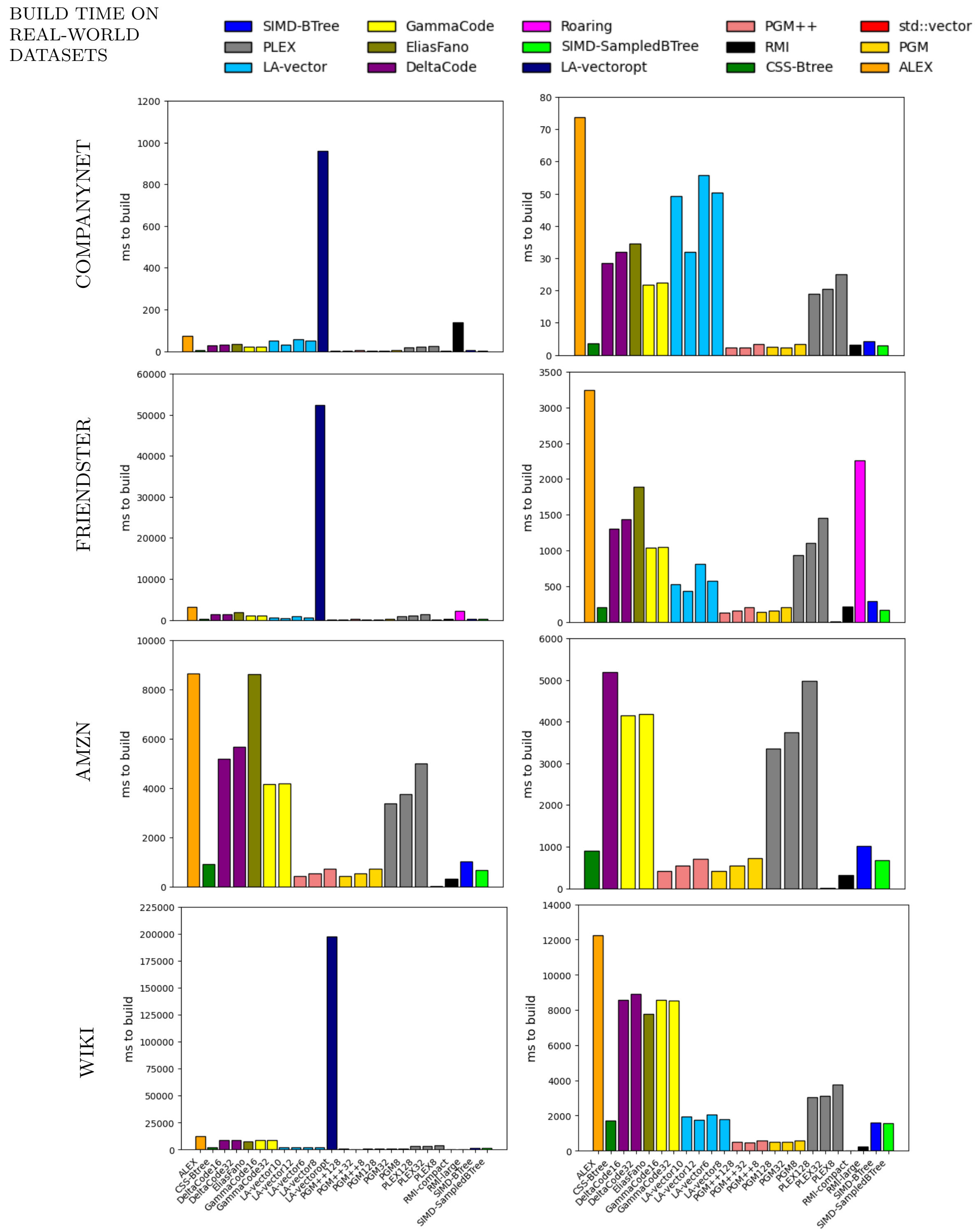


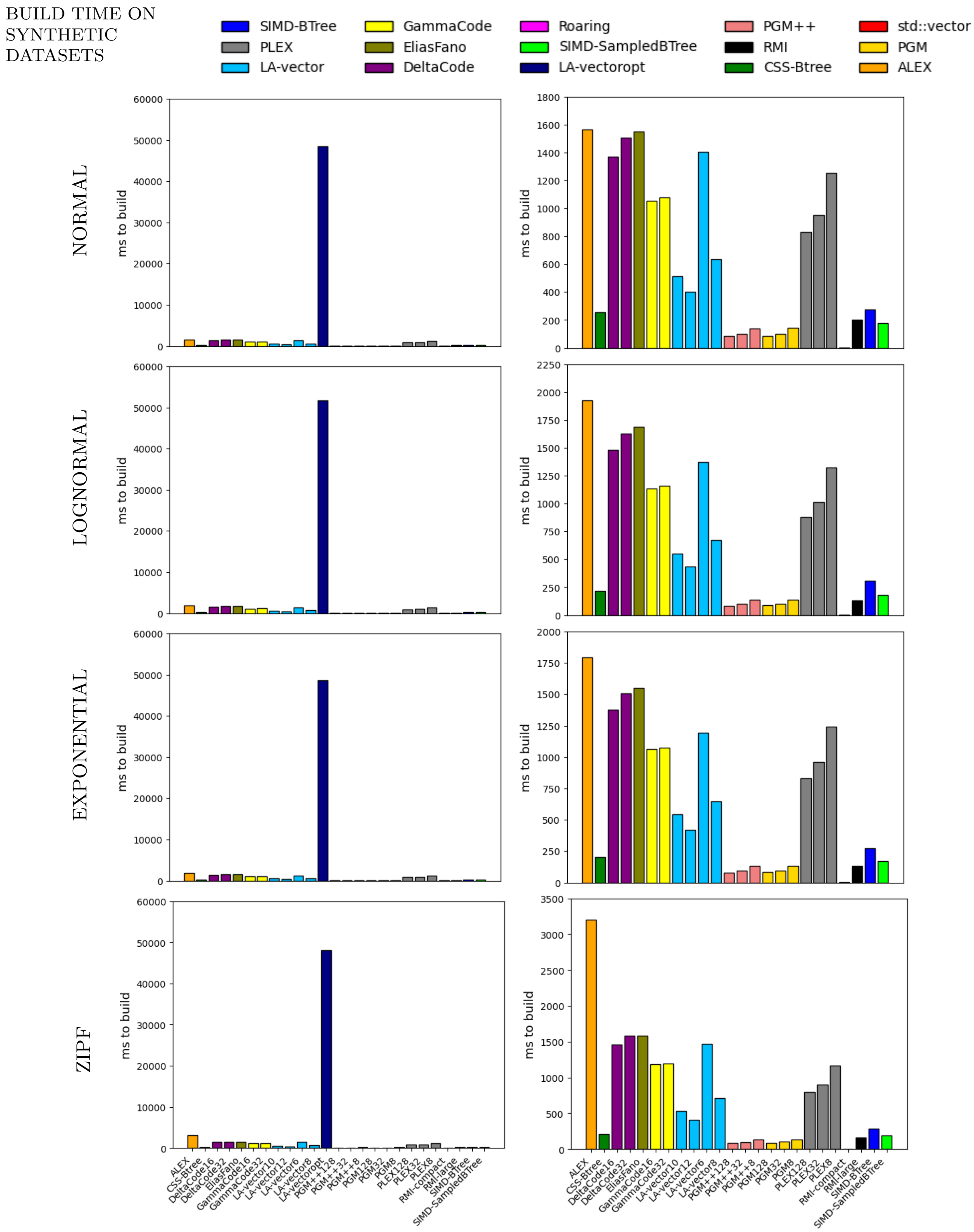
Figure 12: Wiki uint64

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.



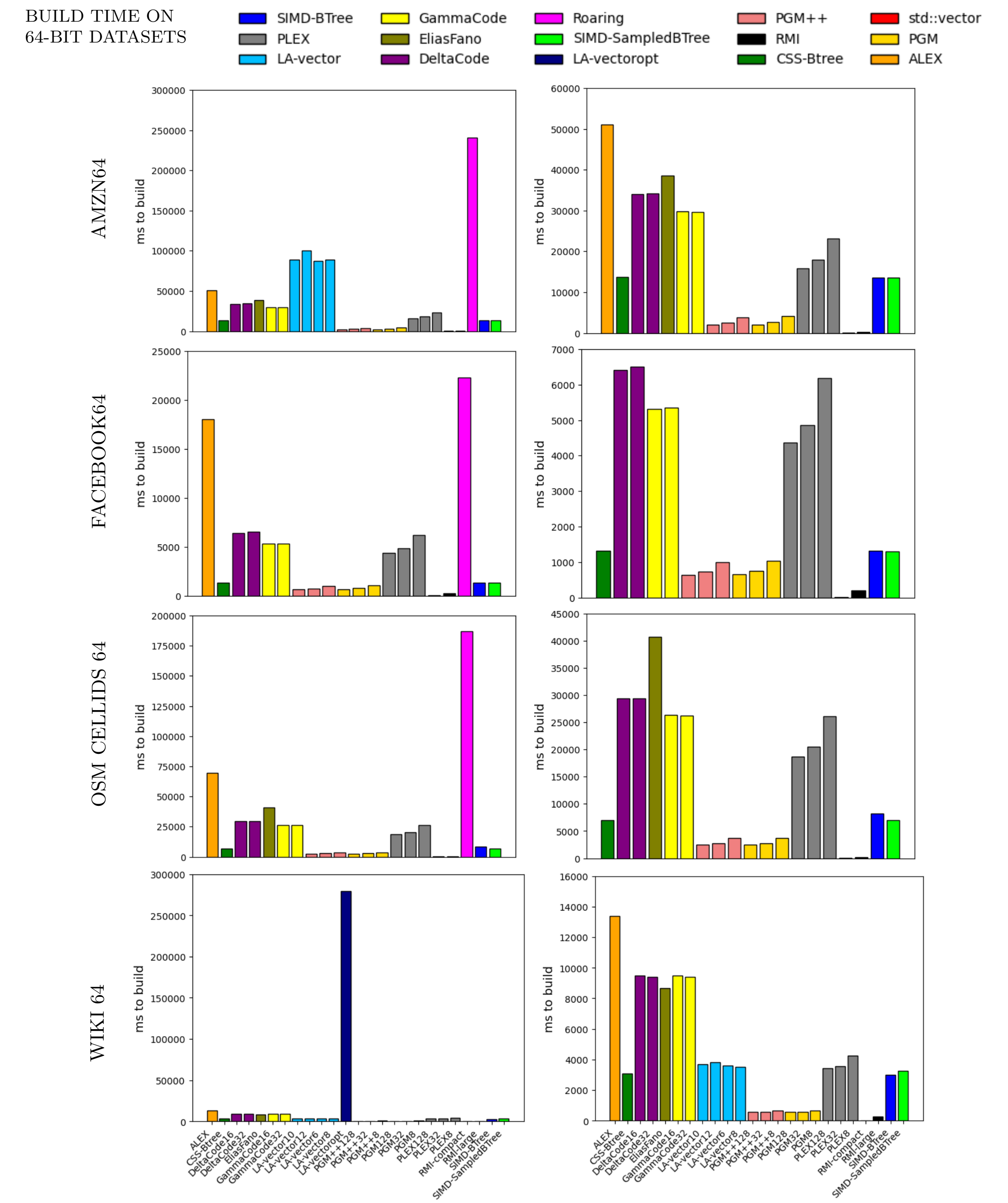
The plots above report the time required to build the data structures (indexes) on the real-world datasets. On the left, the dataset's name is shown; in the middle, the complete plot with all the times expressed in milliseconds; and on the right, the same plot but excluding the ones with excessive build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

Figure 13: Build time on real-world datasets



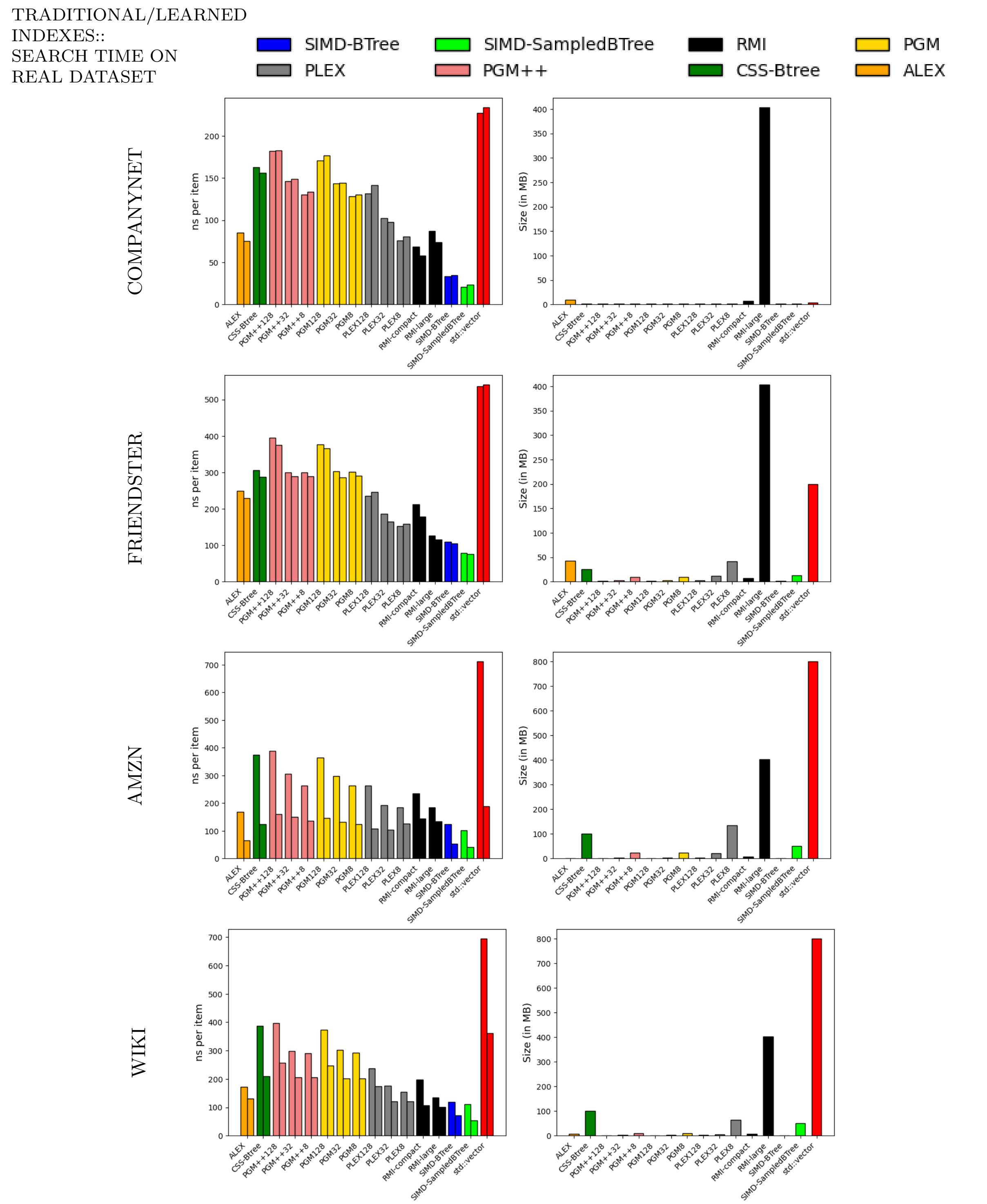
The plots above report the time required to build the data structures (indexes) on the synthetic datasets. On the left, the dataset's name is shown; in the middle, the complete plot with all the times expressed in milliseconds; and on the right, the same plot but excluding the ones with excessive build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

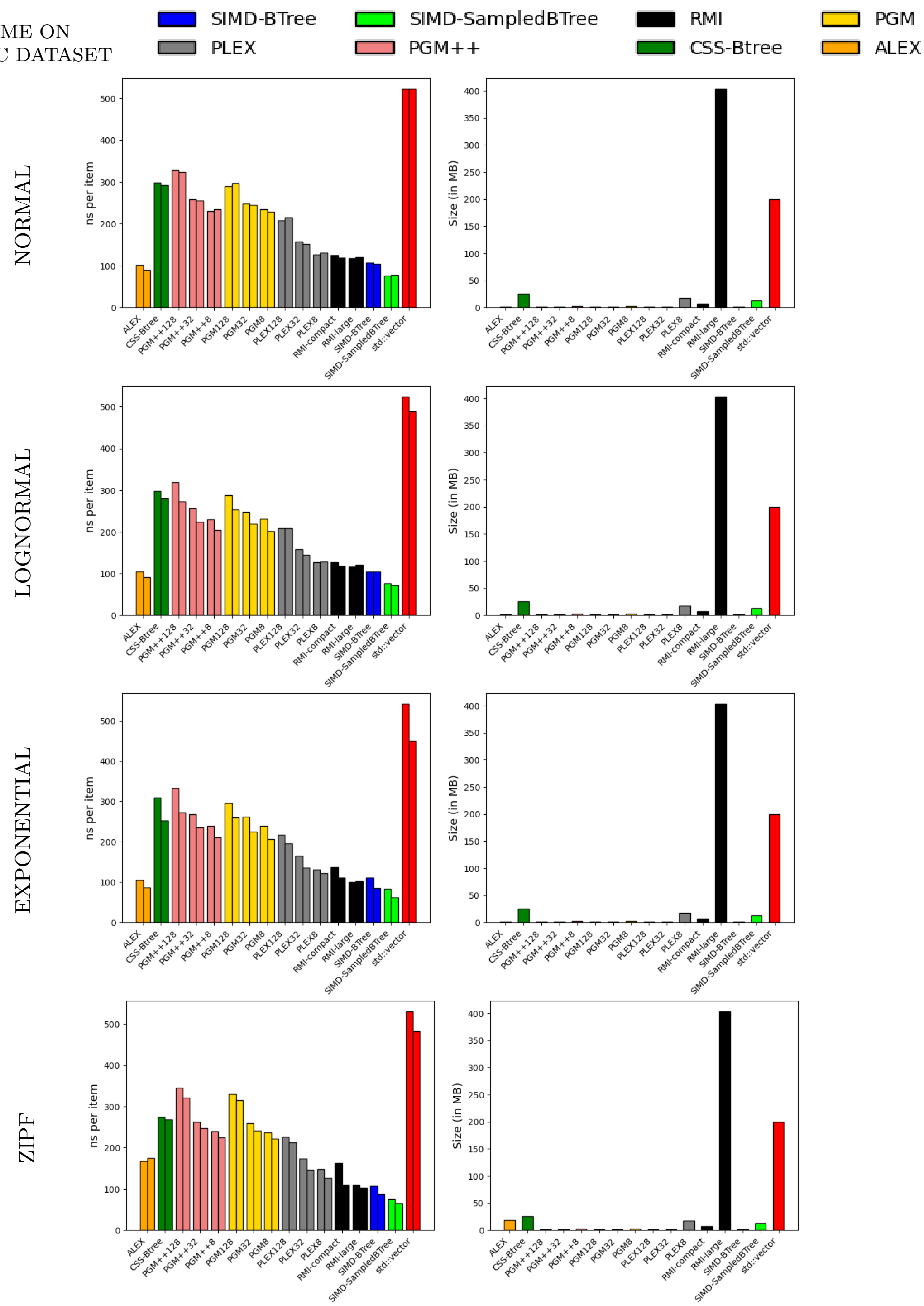
Figure 15: Build time on 64-bit datasets



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.

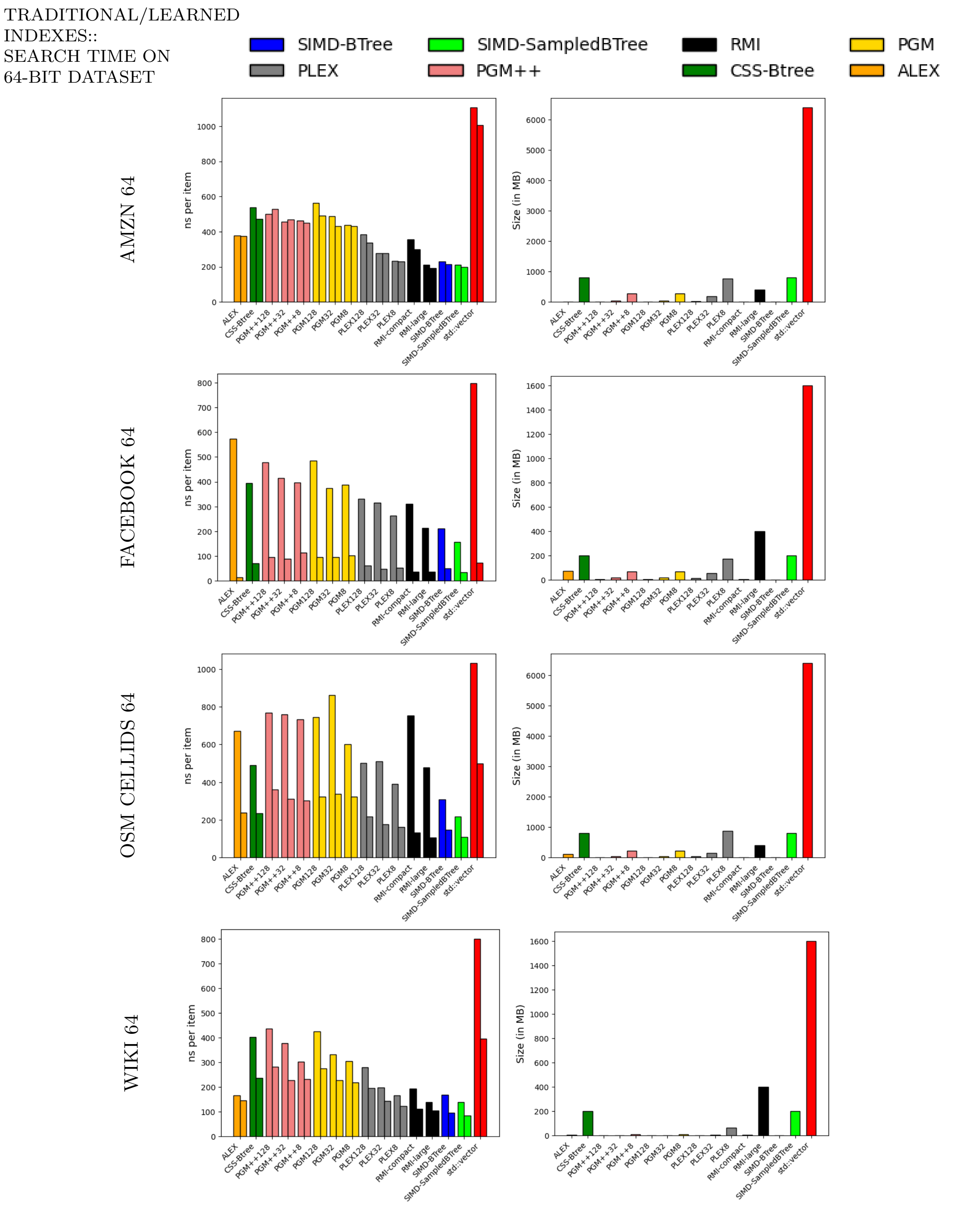
Figure 16: Average time for pointwise queries on traditional and learned indexes, built on real-world datasets.

TRADITIONAL/LEARNED INDEXES:: SEARCH TIME ON SYNTHETIC DATASET



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.

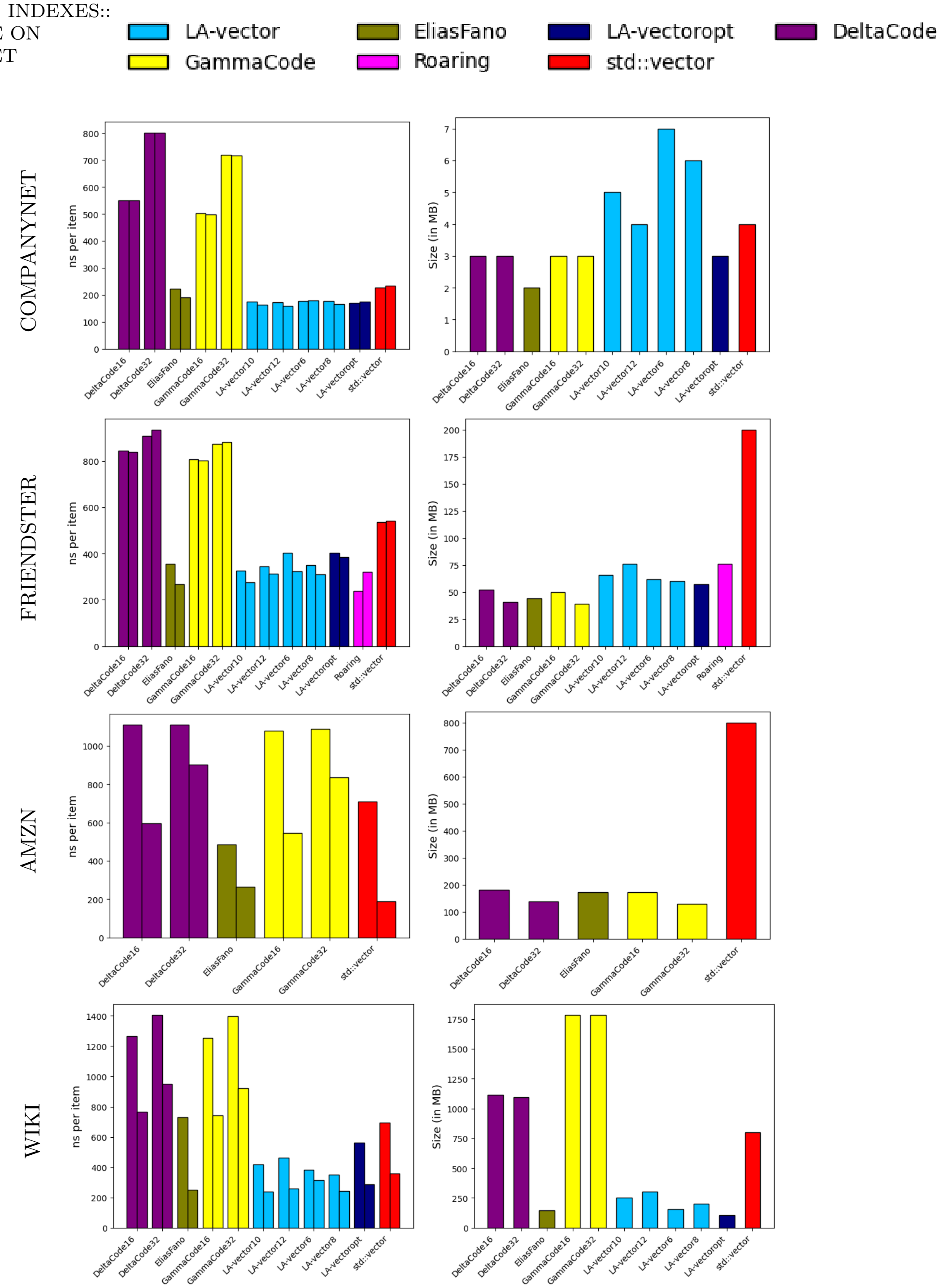
Figure 17: Average time for pointwise queries on traditional and learned indexes, built on synthetic datasets.



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.

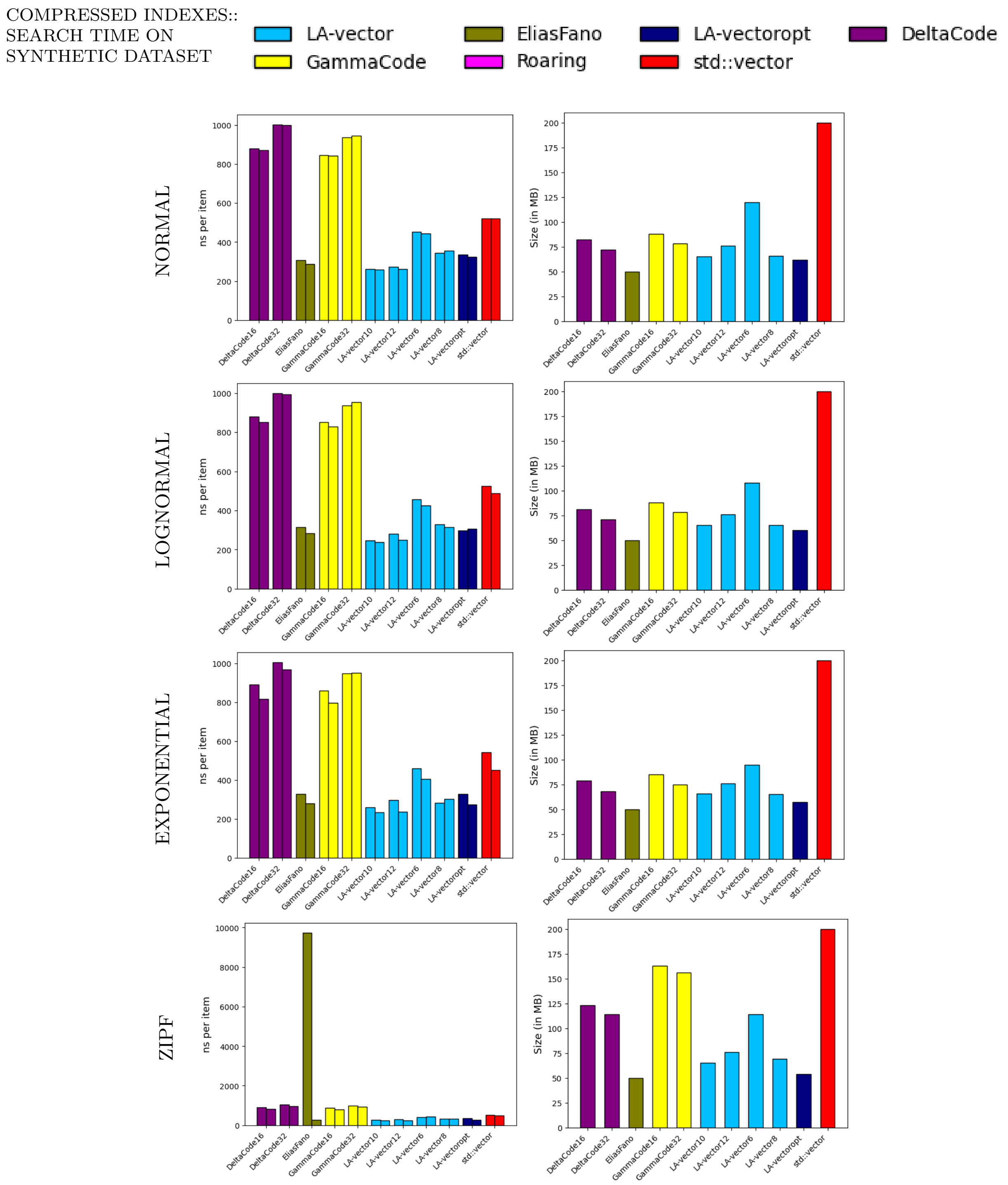
Figure 18: Average time for pointwise queries on traditional and learned indexes, built on 64-bit datasets.

COMPRESSED INDEXES::
SEARCH TIME ON
REAL DATASET



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.

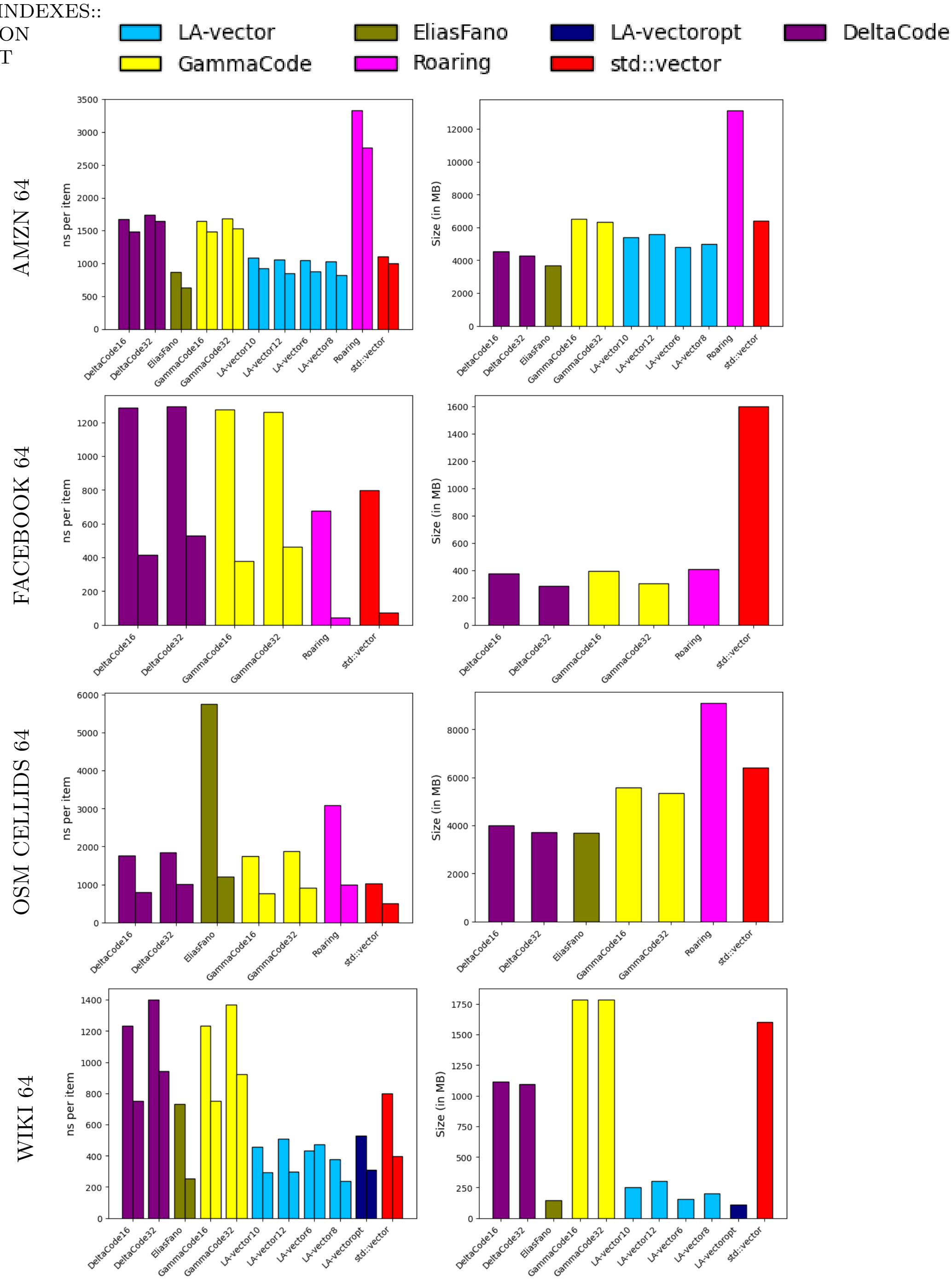
Figure 19: Average time for pointwise queries on compressed indexes, built on real-world datasets.



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.

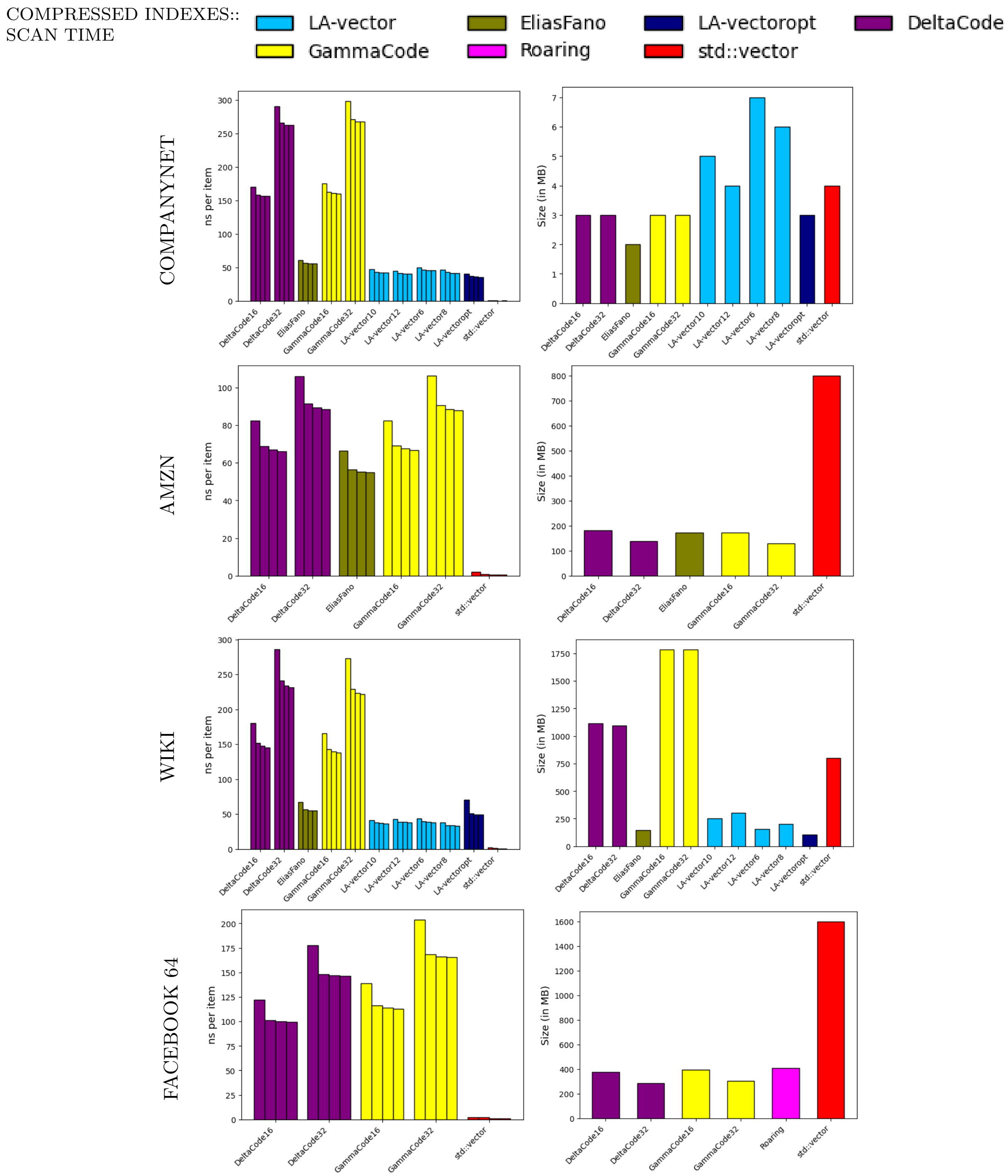
Figure 20: Average time for pointwise queries on compressed indexes, built on synthetic datasets.

COMPRESSED INDEXES::
SEARCH TIME ON
64-BIT DATASET



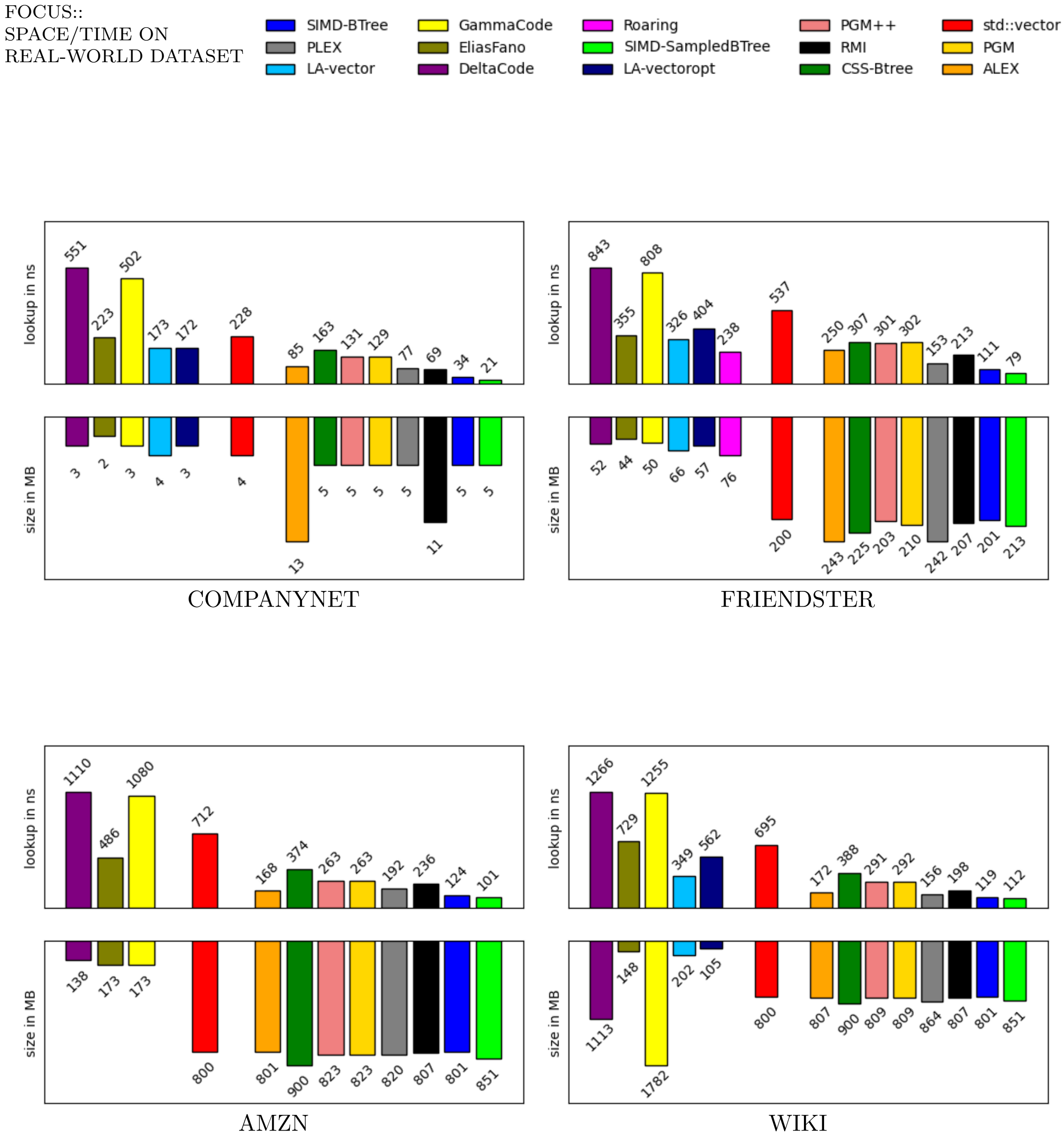
The performances of compressed indexes on 64-bit datasets are represented in two plots. The leftmost plot shows the time of search (in ns) on each index; while the right plot shows the space occupied by each index in MBs (without considering the space occupied by the data to be stored). The left plot 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.



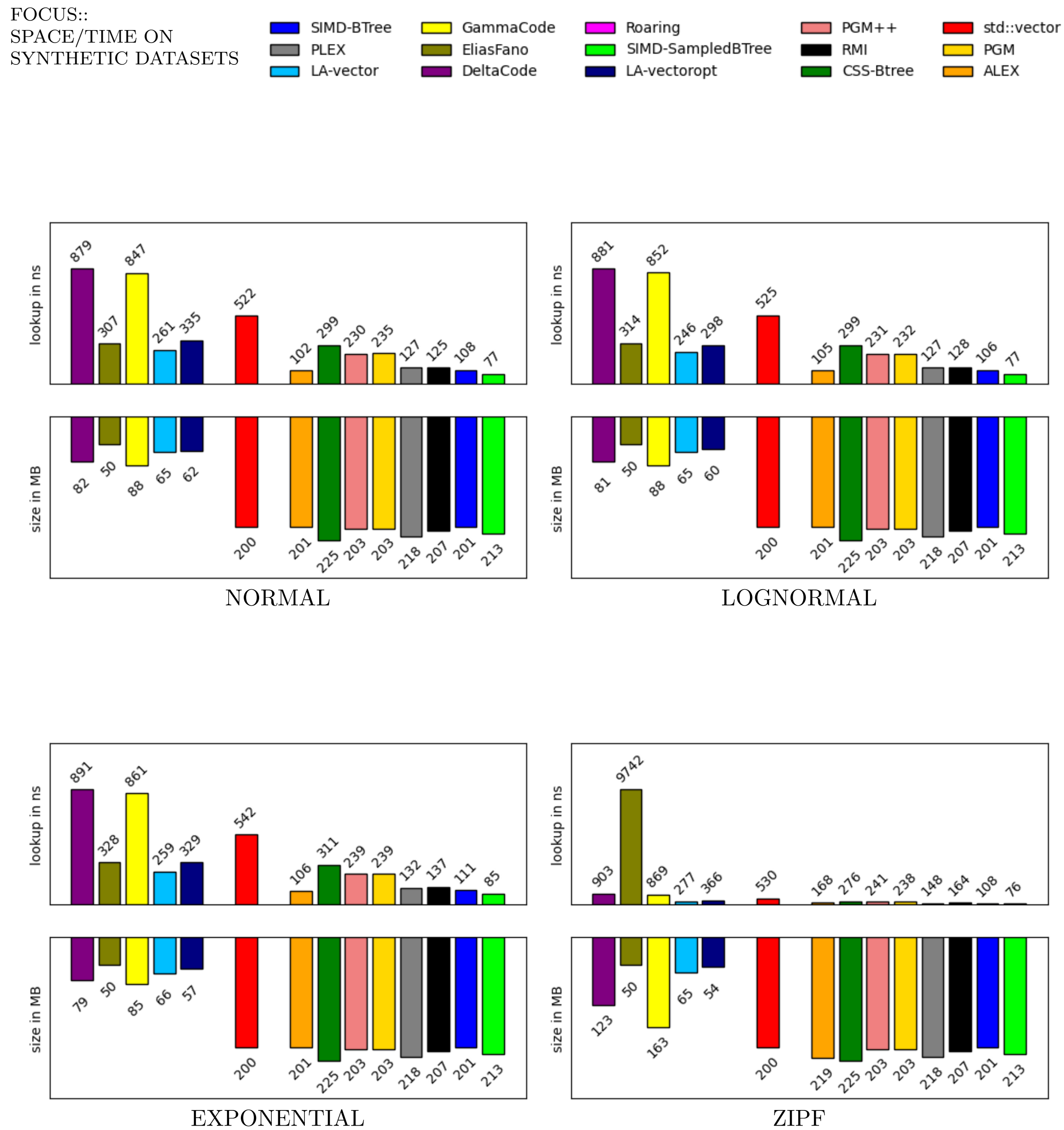
The plots above show the performance of compressed indexes in time and space relative to *range queries*, where starting points are randomly sampled, and the width of the scan is set to 10, 100, 1K, and 10K. The plot on the left shows the time (in ns) required for every interrogation, describing the 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.



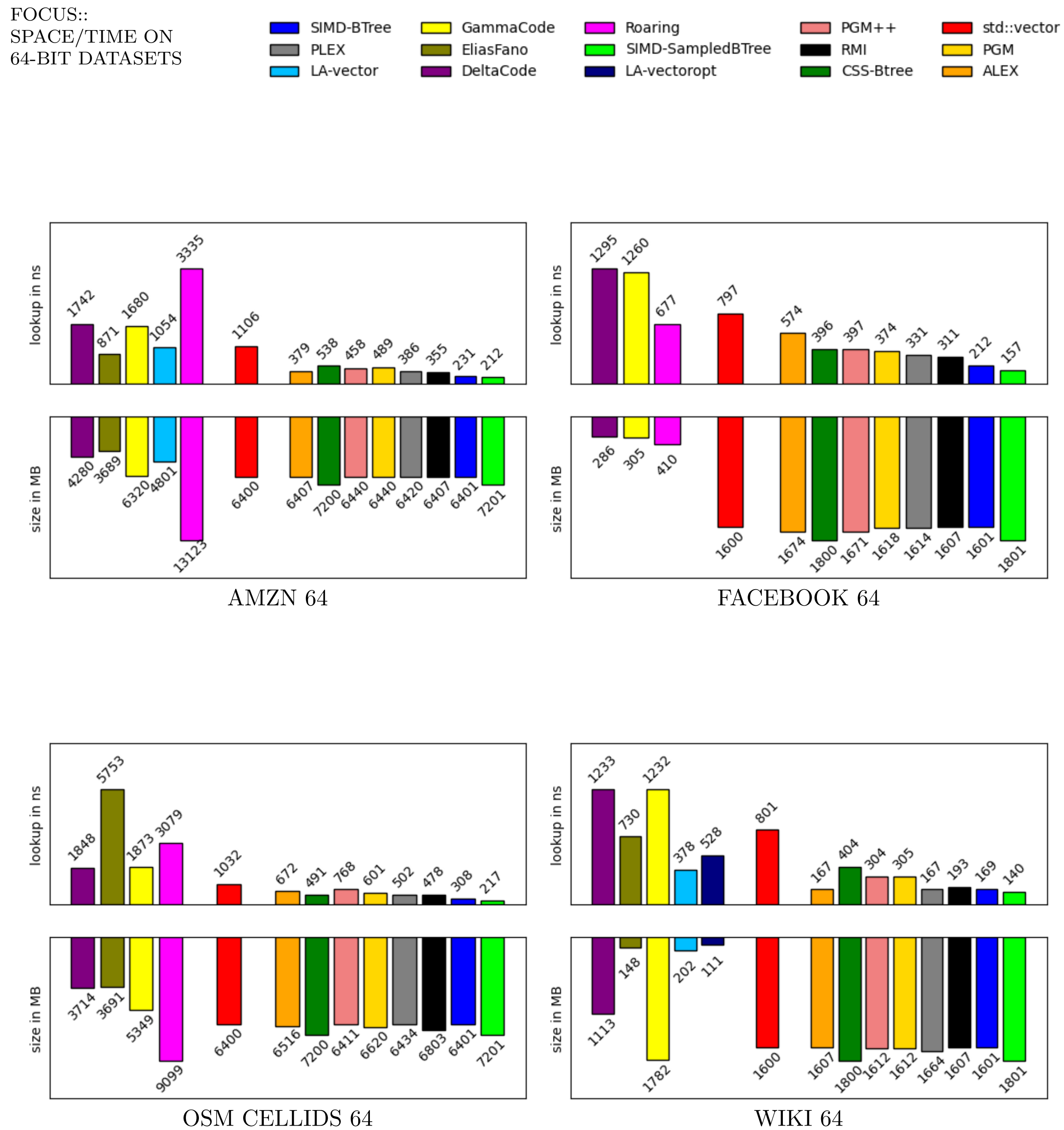
The figures above show the results corresponding to the space occupied and elapsed time for pointwise queries on real-world datasets on all tested indexes (traditional, learned, and compressed). For each dataset and for each index, the top part shows the average time (in ns) needed to make a query on 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.



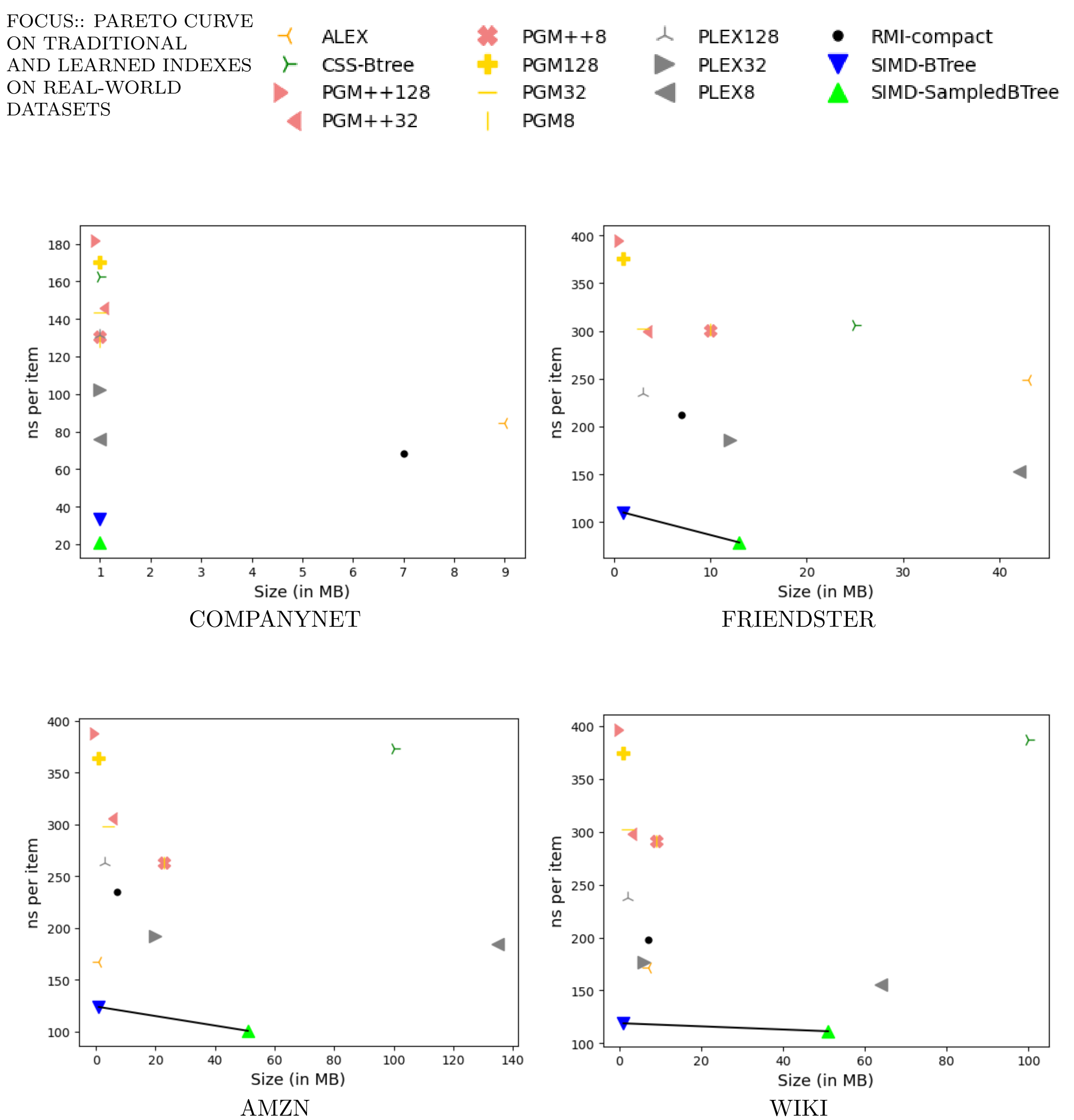
The figures above show the results corresponding to the space occupied and elapsed time for pointwise queries on synthetic datasets on all tested indexes (traditional, learned, and compressed). For each dataset and for each index, the top part shows the average time (in ns) needed to make a query on 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.

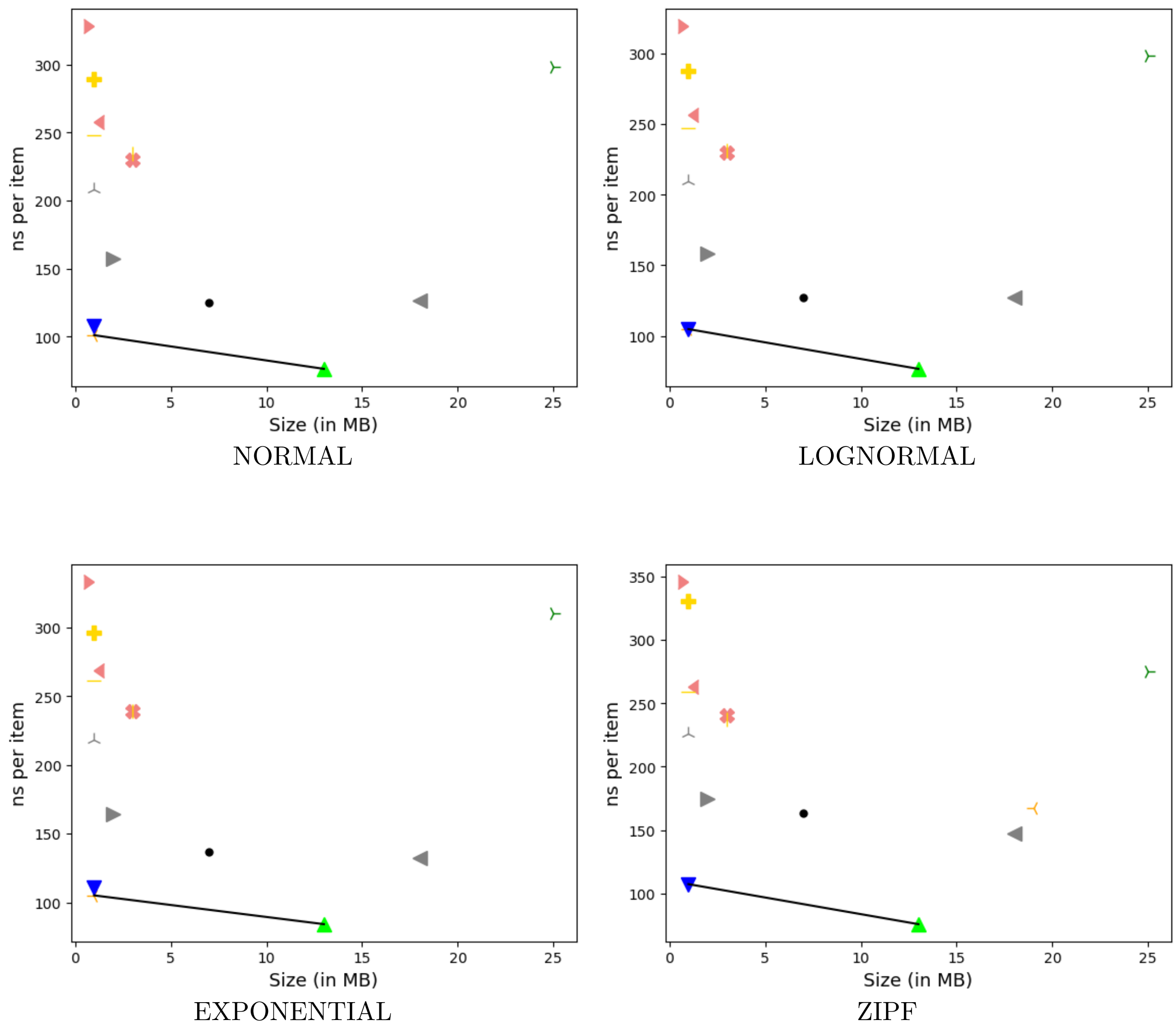


The plots recap the experimental results about occupied space/time needed for pointwise queries for traditional and learned indexes on real-world datasets. For these datasets, for each index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per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

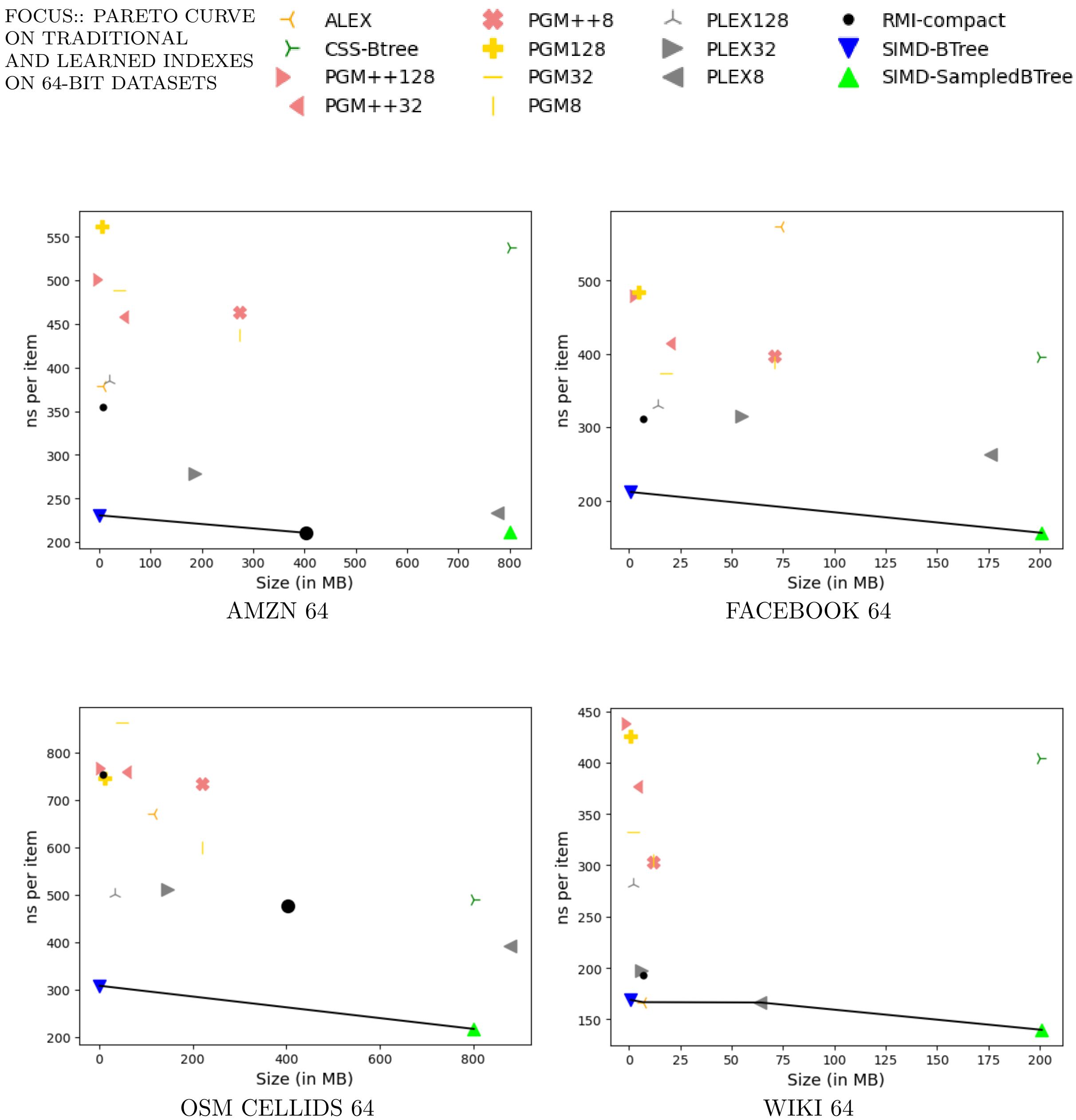
FOCUS:: PARETO CURVE ON TRADITIONAL AND LEARNED INDEXES ON SYNTHETIC DATASETS



The plots recap the experimental results about occupied space/time needed for pointwise queries for traditional and learned indexes on 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

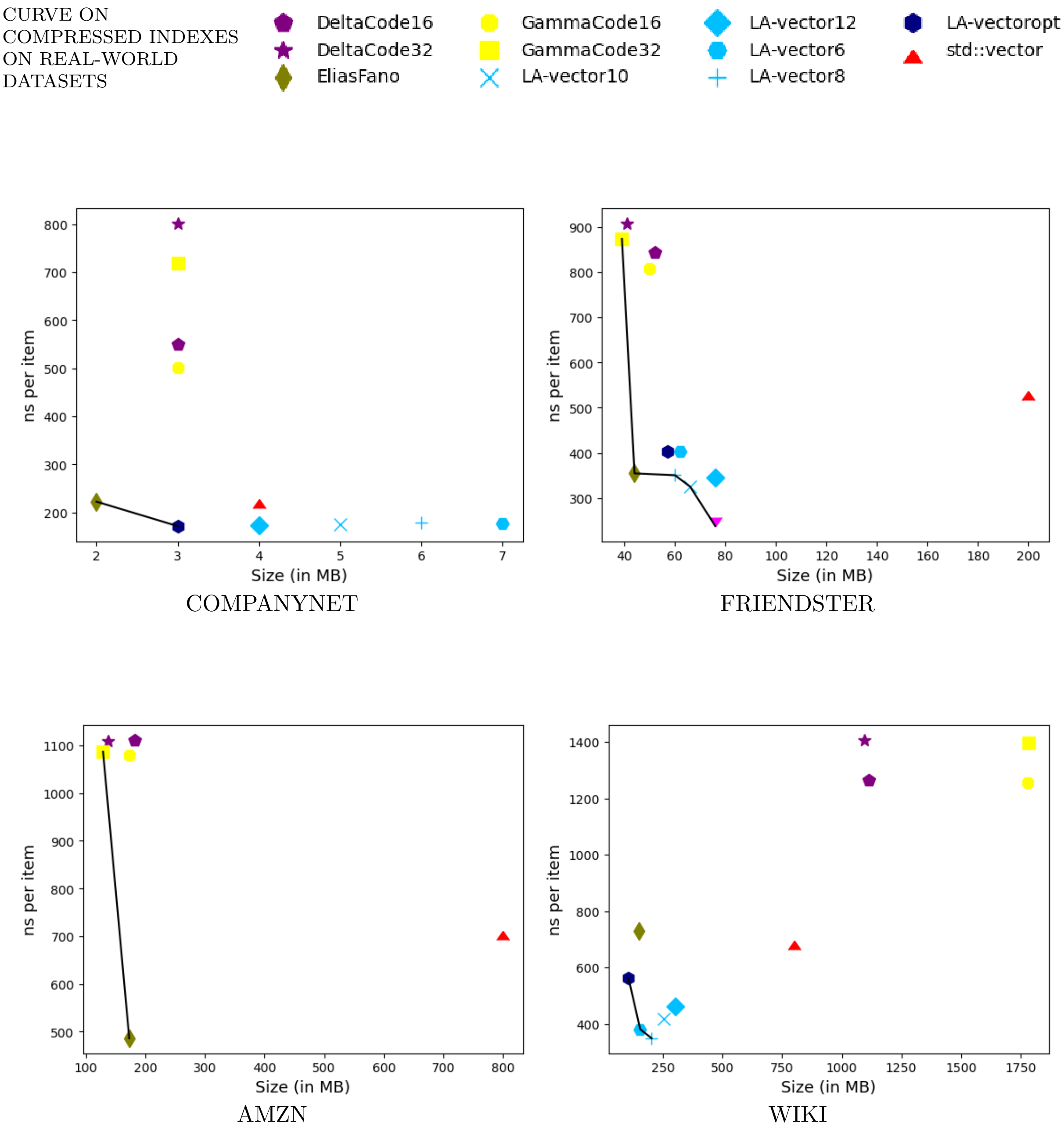


The plots recap the experimental results about occupied space/time needed for pointwise queries for traditional and learned indexes on 64-bit datasets. For these datasets, for each index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise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

FOCUS:: PARETO CURVE ON COMPRESSED INDEXES ON REAL-WORLD DATASETS

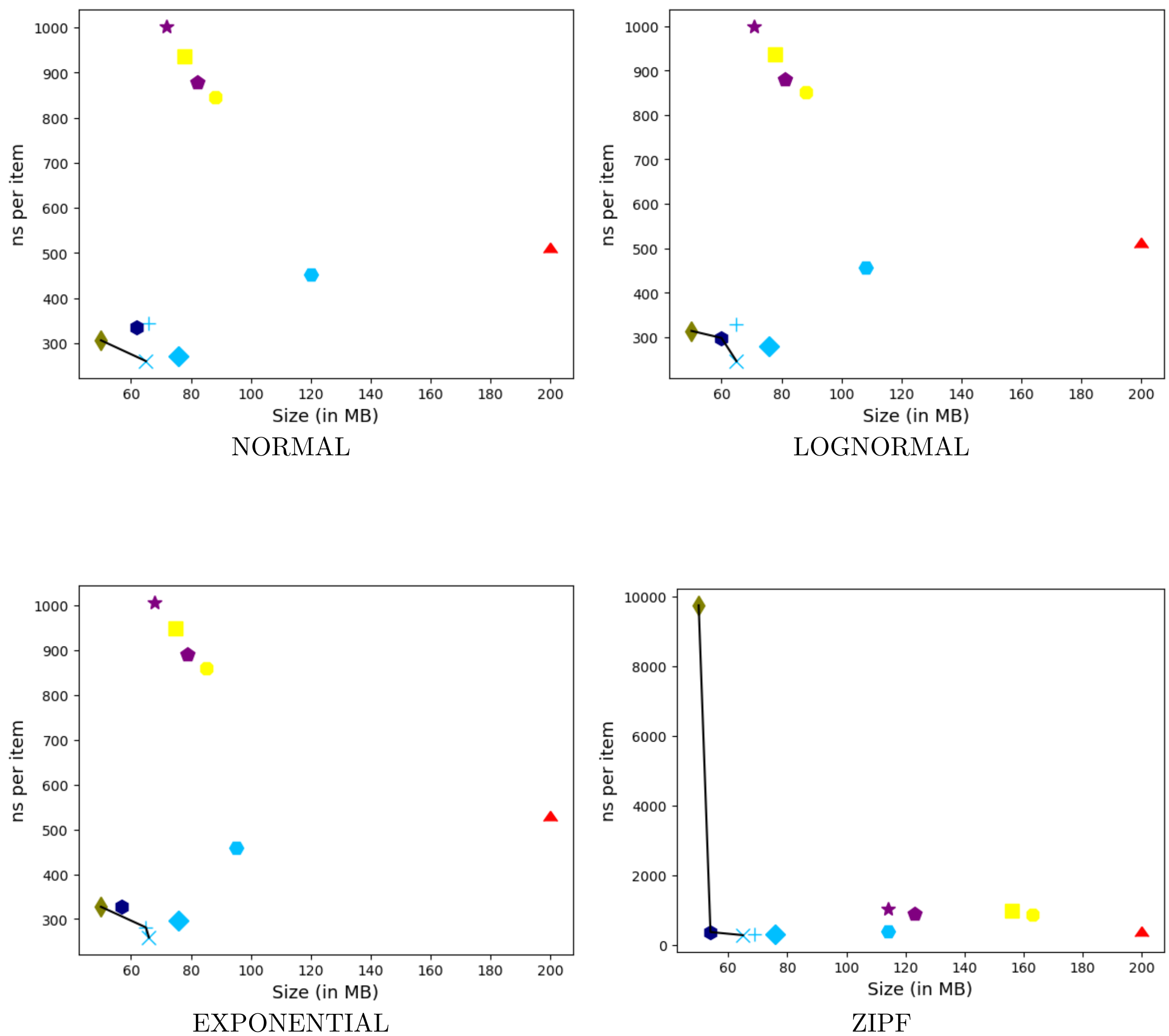


The plots recap the experimental results about occupied space/time needed for pointwise queries for compressed indexes on real-world datasets. For these datasets, for each compressed index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per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

FOCUS:: PARETO CURVE ON COMPRESSED INDEXES ON SYNTHETIC DATASETS

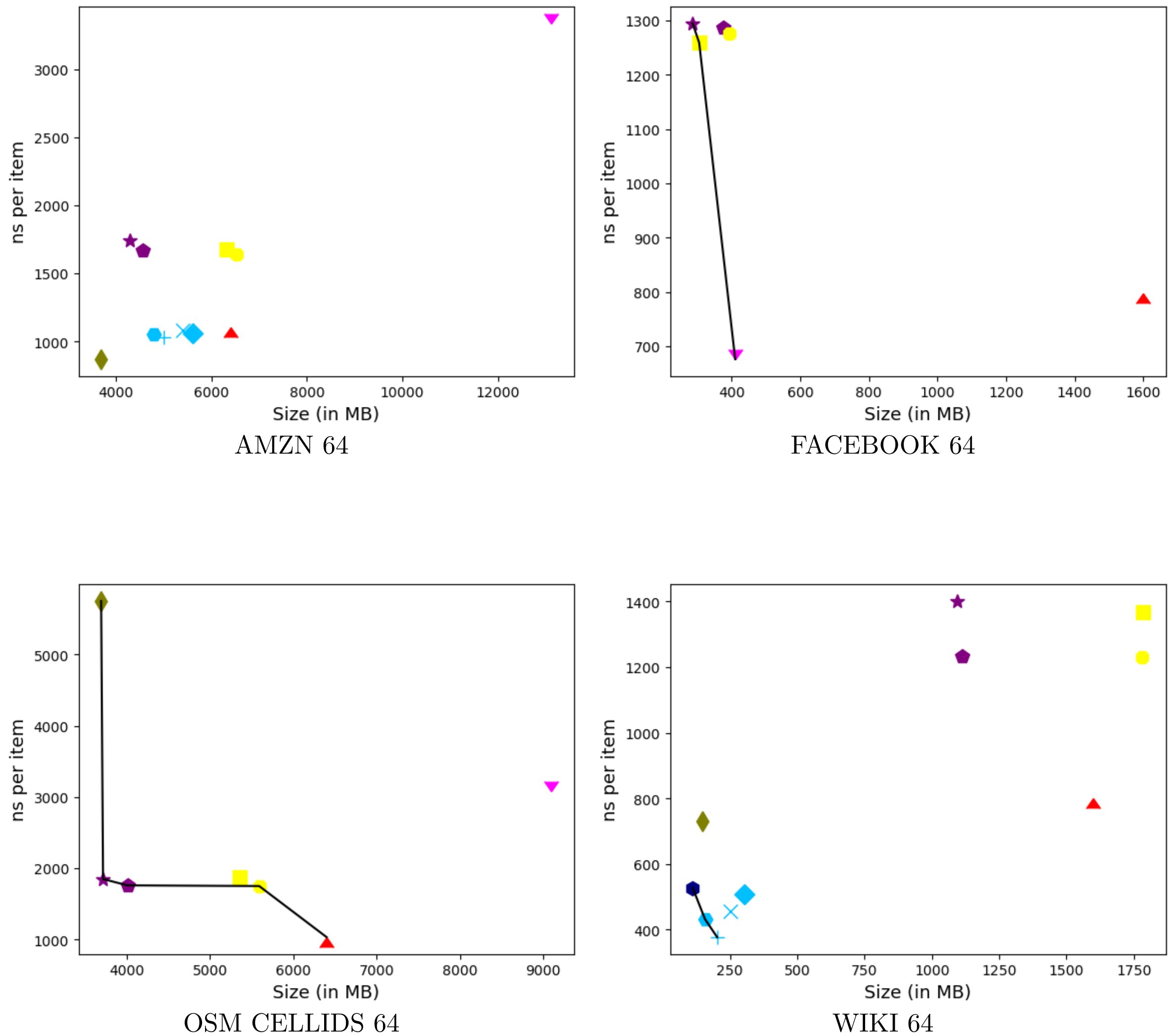


The plots recap the experimental results about occupied space/time needed for pointwise queries for compressed indexes on synthetic datasets. For these datasets, for each compressed index, and each tested configuration we plot the extra space occupied (in MB) on the x-axis, and the time (in ns) per pointwise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

FOCUS:: PARETO CURVE ON COMPRESSED INDEXES ON 64-BIT 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	73.757
CSS-Btree	162.639	156.072	1	3.47303
DeltaCode16	550.163	550.164	3	28.4947
DeltaCode32	801.402	801.772	3	31.9948
EliasFano	222.173	190.123	2	34.5756
GammaCode16	501.978	497.942	3	21.8515
GammaCode32	718.739	716.487	3	22.4363
LA-vector10	174.389	163.978	5	49.1686
LA-vector12	172.844	158.693	4	31.8208
LA-vector6	177.356	179.273	7	55.6362
LA-vector8	177.742	165.176	6	50.2594
LA-vectoropt	171.206	174.05	3	959.086
PGM++128	181.748	182.408	1	2.34623
PGM++32	145.778	148.903	1	2.33863
PGM++8	130.347	133.17	1	3.36725
PGM128	170.391	176.688	1	2.39936
PGM32	143.277	144.125	1	2.3582
PGM8	128.272	129.927	1	3.40615
PLEX128	131.528	141.461	1	18.8695
PLEX32	102.084	97.9293	1	20.4044
PLEX8	76.0505	80.3045	1	24.9302
RMI-compact	68.2063	57.9312	7	3.14833
RMI-large	87.104	73.6292	403	138.054
SIMD-BTree	33.1707	34.8978	1	4.20203
SIMD-SampledBTree	20.9854	23.1505	1	2.84402
std::vector	227.127	233.441	4	0.000196509

Table 1: Tabular data: companynet dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	171.216	130.978	7	12250.3
CSS-Btree	387.456	209.897	100	1706.93
DeltaCode16	1265.27	766.646	1113	8585.24
DeltaCode32	1406.5	951.687	1095	8918.44
EliasFano	728.747	251.374	148	7772.2
GammaCode16	1254.4	743.391	1782	8558.24
GammaCode32	1395.82	923.777	1785	8523.53
LA-vector10	419.032	237.91	251	1924.89
LA-vector12	462.707	258.213	301	1744.62
LA-vector6	380.864	315.315	154	2069.24
LA-vector8	348.619	241.481	202	1795.67
LA-vectoropt	561.527	285.196	105	197674
PGM++128	396.57	256.087	1	486.691
PGM++32	298.428	204.902	2	482.605
PGM++8	290.848	205.049	9	564.017
PGM128	374.152	246.121	1	492.813
PGM32	302.538	201.409	2	493.626
PGM8	291.528	201.788	9	569.178
PLEX128	237.739	174.58	2	3024.15
PLEX32	176.581	121.453	6	3128.08
PLEX8	155.252	120.38	64	3749.19
RMI-compact	197.538	106.451	7	2.84652
RMI-large	135.004	101.825	403	235.648
SIMD-BTree	118.831	71.6056	1	1597.51
SIMD-SampledBTree	111.367	53.0724	51	1569.05
std::vector	694.065	360.534	800	0.000316836

Table 2: Tabular data: wiki uint32 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	249.282	228.425	43	3246.62
CSS-Btree	306.611	287.862	25	202.872
DeltaCode16	842.925	838.148	52	1304.31
DeltaCode32	907.486	935.238	41	1437.65
EliasFano	354.424	268.447	44	1888.67
GammaCode16	807.403	801.357	50	1035.2
GammaCode32	873.273	882.188	39	1042.19
LA-vector10	325.142	276.805	66	526.315
LA-vector12	345.036	313.693	76	434.242
LA-vector6	402.512	323	62	811.986
LA-vector8	350.417	310.847	60	576.623
LA-vectoropt	403.264	384.947	57	52328.7
PGM++128	394.567	375.317	1	131.291
PGM++32	300.058	288.891	3	157.844
PGM++8	300.258	288.922	10	204.42
PGM128	376.135	365.009	1	132.605
PGM32	302.368	286.235	3	159.166
PGM8	301.493	290.429	10	207.479
PLEX128	234.662	246.05	3	935.696
PLEX32	185.963	165.233	12	1099.88
PLEX8	152.585	158.389	42	1453.34
RMI-compact	212.397	177.803	7	1.70732
RMI-large	126.462	116.152	403	210.646
Roaring	237.821	320.745	76	2254.53
SIMD-BTree	110.103	104.483	1	292.077
SIMD-SampledBTree	78.882	74.924	13	169.295
std::vector	536.189	540.293	200	0.000377931

Table 3: Tabular data: friendster dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	105.054	85.9853	1	1793.16
CSS-Btree	310.346	252.282	25	205.264
DeltaCode16	890.872	816.098	79	1375.91
DeltaCode32	1006.65	969.474	68	1508.29
EliasFano	327.316	280.85	50	1548.45
GammaCode16	860.252	798.242	85	1065.69
GammaCode32	949.054	950.769	75	1072.15
LA-vector10	258.936	234.123	66	541.29
LA-vector12	297.423	236.388	76	419.269
LA-vector6	459.798	405.767	95	1195.47
LA-vector8	281.28	303.526	65	648.813
LA-vectoropt	328.516	273.581	57	48586.3
PGM++128	333.256	273.656	1	80.6546
PGM++32	268.757	236.751	1	93.8582
PGM++8	238.733	211.15	3	130.359
PGM128	296.382	260.838	1	81.6738
PGM32	261.463	224.831	1	95.6289
PGM8	238.67	207.413	3	132.733
PLEX128	218.257	196.585	1	831.188
PLEX32	164.447	136.248	2	958.108
PLEX8	131.953	121.509	18	1244.44
RMI-compact	136.908	110.583	7	2.86306
RMI-large	100.939	101.656	403	130.797
SIMD-BTree	110.86	85.3157	1	273.07
SIMD-SampledBTree	84.1393	61.7075	13	169.157
std::vector	541.996	450.289	200	0.000363961

Table 4: Tabular data: exponential dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	104.909	91.3408	1	1925.96
CSS-Btree	298.479	280.769	25	218.561
DeltaCode16	880.698	851.485	81	1481.7
DeltaCode32	999.842	994.071	71	1628.53
EliasFano	313.658	283.585	50	1691
GammaCode16	851.016	828.575	88	1133.47
GammaCode32	937.174	953.315	78	1160.45
LA-vector10	245.619	237.983	65	549.706
LA-vector12	279.572	250.127	76	432.959
LA-vector6	456.651	425.821	108	1374.75
LA-vector8	329.223	314.825	65	673.096
LA-vectoropt	297.824	307.213	60	51735.8
PGM++128	319.303	272.324	1	84.8645
PGM++32	256.398	223.029	1	100.779
PGM++8	230.012	204.547	3	139.745
PGM128	287.646	253.085	1	86.8909
PGM32	246.915	219.002	1	102.837
PGM8	231.244	202.007	3	139.112
PLEX128	209.419	209.191	1	881.072
PLEX32	158.246	145.083	2	1011.73
PLEX8	126.922	128.496	18	1326.59
RMI-compact	127.217	118.769	7	3.23318
RMI-large	116.657	121.766	403	132.918
SIMD-BTree	105.188	104.163	1	307.019
SIMD-SampledBTree	76.7902	71.7349	13	182.324
std::vector	524.067	488.268	200	0.000275858

Table 5: Tabular data: lognormal dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	167.383	175.213	19	3206.53
CSS-Btree	275.09	268.488	25	213.12
DeltaCode16	902.359	823.844	123	1464.73
DeltaCode32	1034.87	966.477	114	1581.43
EliasFano	9741.94	280.261	50	1588.23
GammaCode16	868.381	802.847	163	1189.7
GammaCode32	980.971	928.791	156	1196.68
LA-vector10	276.811	230.765	65	530.067
LA-vector12	299.576	233.954	76	406.322
LA-vector6	399.53	431.715	114	1475.26
LA-vector8	314.007	332.131	69	709.681
LA-vectoropt	365.824	276.092	54	48099.2
PGM++128	345.919	321.539	1	84.5145
PGM++32	262.665	246.796	1	100.503
PGM++8	240.177	224.297	3	136.395
PGM128	330.631	314.629	1	85.9683
PGM32	258.713	240.903	1	102.395
PGM8	237.098	221.211	3	139.217
PLEX128	226.382	212.227	1	795.402
PLEX32	174.259	145.882	2	903.678
PLEX8	147.392	126.838	18	1169.39
RMI-compact	163.43	110.803	7	1.92038
RMI-large	110.573	102.847	403	163.962
SIMD-BTree	107.4	88.0679	1	283.448
SIMD-SampledBTree	75.8451	64.8493	13	189.147
std::vector	529.908	481.796	200	0.00030091

Table 6: Tabular data: zipf dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	101.038	89.5688	1	1566.54
CSS-Btree	298.307	293.062	25	254.656
DeltaCode16	878.739	872.093	82	1372.16
DeltaCode32	1002.53	999.058	72	1507.11
EliasFano	306.291	287.017	50	1552.98
GammaCode16	846.473	843.143	88	1054.83
GammaCode32	935.681	944.724	78	1078.23
LA-vector10	260.203	257.764	65	514.121
LA-vector12	271.374	260.617	76	399.656
LA-vector6	453.085	443.034	120	1404.77
LA-vector8	344.367	356.074	66	633.303
LA-vectoropt	334.535	324.737	62	48471.2
PGM++128	328.339	323.115	1	85.1016
PGM++32	258.105	254.79	1	100.473
PGM++8	229.672	234.455	3	136.707
PGM128	289.289	297.185	1	86.4902
PGM32	248.307	244.356	1	99.0724
PGM8	234.847	229.159	3	141.955
PLEX128	207.873	215.56	1	829.771
PLEX32	157.443	151.75	2	953.041
PLEX8	126.653	131.623	18	1254.72
RMI-compact	124.905	118.324	7	1.97878
RMI-large	117.204	120.689	403	200.492
SIMD-BTree	107.516	103.903	1	273.753
SIMD-SampledBTree	76.2583	77.1358	13	179.501
std::vector	521.889	521.671	200	0.000394881

Table 7: Tabular data: normal dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	167.491	65.8118	1	8640.33
CSS-Btree	373.425	122.897	100	895.002
DeltaCode16	1111.35	594.898	182	5179.6
DeltaCode32	1109.42	901.669	138	5678.04
EliasFano	485.996	263.342	173	8624.73
GammaCode16	1079.56	545.488	173	4141.61
GammaCode32	1086.91	836.371	129	4184.85
PGM++128	387.687	160.025	1	408.786
PGM++32	306.026	149.758	4	538.527
PGM++8	262.989	136.68	23	710.456
PGM128	363.67	145.096	1	413.025
PGM32	297.806	130.935	4	540.04
PGM8	262.699	124.676	23	718.454
PLEX128	263.166	108.248	3	3356.92
PLEX32	191.716	102.956	20	3736.08
PLEX8	184.065	125.158	135	4980.63
RMI-compact	235.018	143.763	7	4.17444
RMI-large	184.596	134.513	403	316.373
SIMD-BTree	123.756	53.5838	1	1019.2
SIMD-SampledBTree	100.765	41.9515	51	666.576
std::vector	711.094	188.601	800	0.000350364

Table 8: Tabular data: amzn uint32 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	378.669	375.659	7	51129.6
CSS-Btree	537.161	473.147	800	13740.9
DeltaCode16	1669.93	1486.91	4554	34080.4
DeltaCode32	1741.05	1641.7	4280	34163.2
EliasFano	870.018	633.128	3689	38514.7
GammaCode16	1641.88	1480.54	6529	29730.1
GammaCode32	1679.7	1529.27	6320	29658.6
LA-vector10	1083.72	930.558	5401	88643.9
LA-vector12	1062.75	852.285	5601	99877.4
LA-vector6	1053.73	879.114	4801	87544.7
LA-vector8	1033.01	825.049	5001	88549
PGM++128	501.538	528.537	5	2045.27
PGM++32	457.759	468.919	40	2536.9
PGM++8	463.501	449.182	273	3789.16
PGM128	561.801	490.928	5	2093.48
PGM32	488.42	431.021	40	2606.65
PGM8	437.634	429.747	273	4060.13
PLEX128	385.164	337.635	20	15909.1
PLEX32	278.458	276.138	186	17986.7
PLEX8	233.454	229.739	775	23171.5
RMI-compact	354.264	297.817	7	2.93933
RMI-large	210.585	193.132	403	193.07
Roaring	3334.82	2763.85	13123	240789
SIMD-BTree	230.589	213.628	1	13592.8
SIMD-SampledBTree	211.211	198.361	801	13623.6
std::vector	1105.49	1005.29	6400	0.00035977

Table 9: Tabular data: amzn uint64 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	671.084	237.645	116	69691.4
CSS-Btree	490.232	234.792	800	6953.19
DeltaCode16	1758.77	794.365	4007	29418.3
DeltaCode32	1847.87	1004.56	3714	29451.8
EliasFano	5752.57	1206.97	3691	40745.9
GammaCode16	1749.51	771.32	5589	26382.1
GammaCode32	1872.32	918.599	5349	26258
PGM++128	767.681	361.784	11	2465.78
PGM++32	759.417	310.022	48	2747.44
PGM++8	733.479	302.344	220	3698.03
PGM128	745.425	323.391	11	2458.18
PGM32	863.109	338.437	48	2775.28
PGM8	600.297	324.233	220	3746.43
PLEX128	501.306	216.359	34	18646
PLEX32	510.674	175.989	147	20487.8
PLEX8	390.956	160.757	879	26167.9
RMI-compact	754.173	131.459	7	2.33918
RMI-large	477.233	107.309	403	194.959
Roaring	3078.13	984.998	9099	187146
SIMD-BTree	307.941	148.401	1	8230.16
SIMD-SampledBTree	216.965	109.716	801	6987.79
std::vector	1031.15	497.749	6400	0.00029644

Table 10: Tabular data: OSM cellids dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	166.736	146.297	7	13391.5
CSS-Btree	403.955	236.624	200	3081.4
DeltaCode16	1232.16	752.528	1113	9473.72
DeltaCode32	1401.09	941.488	1095	9415.49
EliasFano	729.419	255.153	148	8688.64
GammaCode16	1231.34	752.246	1782	9503.45
GammaCode32	1366.65	921.002	1785	9399.67
LA-vector10	455.316	294.902	251	3677.02
LA-vector12	506.993	296.99	301	3804.49
LA-vector6	431.688	470.686	157	3600.5
LA-vector8	377.027	237.212	202	3514.79
LA-vectoropt	527.244	309.344	111	279103
PGM++128	438.115	282.648	1	563.241
PGM++32	376.922	227.561	2	559.212
PGM++8	303.329	232.349	12	645.531
PGM128	425.689	275.343	1	583.744
PGM32	332.312	227.73	2	575.504
PGM8	304.436	218.545	12	674.349
PLEX128	281.411	195.393	2	3419.38
PLEX32	197.446	143.372	6	3555.53
PLEX8	166.412	123.024	64	4248.39
RMI-compact	192.971	111.758	7	3.77417
RMI-large	140.415	106.22	403	290.662
SIMD-BTree	168.845	96.0625	1	2983.48
SIMD-SampledBTree	139.777	83.8916	201	3248.17
std::vector	800.183	396.749	1600	0.000284985

Table 11: Tabular data: wiki uint64 dataset

index	lookup existing (ns)	lookup missing (ns)	space (MB)	build (ms)
ALEX	573.6	14.5306	74	18045.2
CSS-Btree	395.47	70.4056	200	1310.87
DeltaCode16	1287.61	414.694	374	6417.91
DeltaCode32	1294.78	527.001	286	6509.4
GammaCode16	1275.4	377.475	393	5320.56
GammaCode32	1259.13	461.428	305	5343.31
PGM++128	479.12	95.6022	5	634.277
PGM++32	414.727	89.9523	18	730.322
PGM++8	396.81	113.925	71	1003.54
PGM128	484.534	96.599	5	653.159
PGM32	373.327	94.9386	18	753.238
PGM8	388.017	101.629	71	1023.94
PLEX128	330.364	61.1977	14	4366.79
PLEX32	315.18	49.0181	55	4848.92
PLEX8	262.922	52.3193	176	6190.32
RMI-compact	310.753	37.2934	7	2.34779
RMI-large	213.143	37.4332	403	207.782
Roaring	676.09	44.9812	410	22295.9
SIMD-BTree	211.628	50.3897	1	1318.88
SIMD-SampledBTree	156.053	33.8489	201	1299.44
std::vector	796.749	72.0668	1600	0.000298861

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
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
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
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
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
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
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
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
```