Table 1. The categorization of experimental settings in the collected papers. (Part one)

Aspect	Factors	Options	Papers
Evaluation metrics	Metrics incorporated in evaluation	Recall	[32] [93] [23] [66] [25] [74] [67] [82] [64] [70] [48] [16] [40] [4] [86] [85] [29] [44] [53]
		Hit	[10] [7] [25] [20] [15] [76] [21] [59] [88] [13] [72] [75] [84] [12] [18] [45] [1] [87] [46] [85] [42] [77]
		NDCG	[23] [66] [7] [25] [74] [20] [15] [67] [76] [21] [82] [59] [70] [13] [72] [75] [84] [30] [12] [48] [16] [45] [1] [40] [46] [4] [85] [42] [77] [53]
		AUC	[7] [48]
		Beyond-Accuracy	[18] [93]
	Sampled metrics	Sampled	[32] [23] [15] [76] [21] [59] [72] [84] [12] [45] [1] [87] [46] [44] [42] [77]
		Non-sampled	[93] [10] [66] [7] [25] [20] [67] [64] [70] [88] [13] [75] [30] [81] [16] [4] [86] [29] [85] [53]
Dataset construction	Number of used datasets	≥ 3	[10] [23] [66] [74] [20] [15] [67] [82] [64] [59] [70] [88] [75] [84] [30] [12] [48] [18] [16] [45] [1] [40] [46] [4] [86] [42]
		<3	[32] [93] [7] [25] [76] [21] [13] [72] [81] [87] [85] [29] [44] [77] [53]
	Dataset filtering	*n*-core filtering	[32] [93] [66] [7] [25] [67] [20] [21] [82] [59] [88] [13] [72] [84] [81] [12] [18] [16] [1] [40] [4] [86] [85] [29] [42] [77]
		Original or neglection	[23] [74] [15] [76] [64] [70] [75] [30] [48] [45] [87] [46] [44] [53]
	Dataset splitting	RO_RS	[23] [66] [25] [74] [67] [82] [64] [70] [30] [81] [16] [40] [87] [4] [86] [85] [29] [44] [42]
		RO_LS	[32] [10] [20] [76] [88] [48] [18] [45] [46] [53]
		TO_RS	[93] [7] [74]
		TO_LS	[15] [20] [76] [21] [59] [13] [72] [75] [84] [12] [1]
Model optimization	Objective function	BPR-based	[66] [7] [25] [20] [15] [67] [76] [82] [59] [70] [13] [75] [81] [48] [1] [4] [85] [29] [44] [77] [53]
		BCE-based	[93] [10] [23] [74] [21] [64] [84] [30] [12] [45] [86] [42]
	Hyper-parameters	Reported	[32] [10] [7] [74] [67] [64] [88] [30] [81] [16] [1] [40] [85] [29]
		Not reported	[93] [23] [66] [25] [20] [21] [76] [15] [82] [59] [70] [13] [75] [72] [84] [12] [48] [45] [46] [4] [86] [44] [42] [77] [53]

Table 2. The categorization of experimental settings in the collected papers. (Part two)

Aspect	Factors	Options	Papers
Evaluation metrics	Metrics incorporated in evaluation	Recall	[57] [63] [41] [68] [73] [22] [43] [3] [63] [5] [39] [65] [14] [31] [34] [51] [60] [92] [49] [37] [90] [47] [52] [62] [58] [38] [71]
		Hit	[6] [78] [8] [80] [9] [26] [79] [83] [11] [28]
		NDCG	[41] [6] [78] [2] [68] [43] [3] [80] [39] [36] [91] [9] [26] [19] [79] [17] [65] [83] [33] [34] [69] [24] [51] [60] [49] [37] [11] [35] [52] [58] [38] [71]
		AUC	[89] [73] [55] [54] [61] [33] [27] [50]
	Sampled metrics	Sampled	[41] [8] [43] [80] [9] [26] [79] [83] [69] [24] [11] [71]
		Non-sampled	[68] [22] [3] [39] [19] [17] [61] [31] [60] [90] [58] [28]
Dataset construction	Number of used datasets	≥ 3	[63] [41] [8] [68] [73] [22] [63] [5] [55] [80] [36] [9] [26] [54] [65] [14] [61] [31] [34] [69] [60] [92] [37] [11] [52] [50] [62] [58] [28] [38] [71]
		<3	[57] [89] [6] [78] [2] [43] [3] [39] [91] [19] [17] [83] [33] [24] [51] [56] [49] [90] [27] [47] [35]
	Dataset filtering	*n*-core filtering	[41] [6] [78] [68] [22] [43] [5] [80] [39] [36] [9] [26] [79] [92] [11] [47] [35] [50] [58] [28] [38] [71]
		Original or neglection	[57] [63] [89] [2] [8] [73] [63] [91] [17] [65] [14] [83] [61] [31] [34] [69] [24] [51] [60] [56] [49] [37] [90] [27] [52] [62]
	Dataset splitting	RO_RS	[57] [41] [2] [68] [22] [3] [63] [5] [36] [19] [17] [65] [14] [61] [31] [34] [69] [24] [92] [49] [90] [47] [52] [62] [38]
		RO_LS	[8] [28]
		TO_RS	[91] [56] [27] [58] [71]
		TO_LS	[6] [78] [43] [80] [9] [26] [79] [83] [11]
Model optimization	Objective function	BPR-based	[89] [6] [78] [68] [22] [43] [3] [63] [5] [55] [33] [92] [49] [11] [27] [47]
		BCE-based	[57] [63] [41] [8] [80] [36] [9] [26] [19] [79] [54] [65] [34] [69] [24] [56] [50] [62] [58] [38] [71]
	Hyper-parameters	Reported	[63] [41] [8] [68] [63] [22] [39] [79] [54] [65] [14] [33] [69] [90] [47] [38]
		Not reported	[57] [89] [6] [78] [2] [73] [43] [3] [5] [55] [80] [36] [91] [9] [26] [19] [17] [83] [61] [31] [34] [24] [51] [60] [92] [56] [49] [37] [11] [27] [35] [52] [50] [62] [58] [28] [71]

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