1. *K-means variants.* [152], [151], [146], [149], [137], [96], [90], [31], [87], [140], [134], [49], [57], [19], [70], [183], [28], [34], [58], [110], [125], [99], [173]
2. *Spectral clustering.* [85], [50], [95], [18], [156], [154], [155], [182], [20], [117], [118], [44], [62], [179], [61], [45], [113], [114], [132]
3. *Other clustering algorithms.* hierarchical clustering [54], [162], [72], [73], [168], [80], DBSCAN [65], [120], density-based clustering [165], [136], [107], mean-shift [21],[147], neural network-based [89], multi-view and multi-source clustering [158], [27], [71], [40], or model selection [130]
4. *Cluster ensembles.* [17], [167], [157], [63], [92], [105], [174], [143], [175], [133], [88], [77], [63], [124], [60], [68], [93], [162], [166], [170], [176]
5. *Deep learning methods.* [92], [111], [44], [138], [137], [148], [161], [133], [103], [115], [178]
6. *Soft computing approaches.* fuzzy k-means [78], [15], [104], [66], [116], evidential k-means [22], [23], evolutionary approaches[126], [74], [76], [75], [119], [116] ant colony optimisation [171]
7. *Learning a distance metric.* [141],[29], [30], [98], [163], [48], [37], [86], [172], [153], [111], [81], [14],
8. *Incorporating the constraints into the criterion function.* [59], [55], [129], [32], [84], [121], [69], [37], [33], [100], [46], [51], [53], [26], [41], [56], [35], [122], [142], [123], [127], [53], [52], [106], [97]
9. *Active learning, user interaction, incremental clustering.* [154], [169], [109], [112], [67], [16], [43], [25], [42], [47], [131], [139], [150], [168]
10. *Applications.* In addition to the theoretical and algorithmic advances in constrained clustering, we came across a beautiful variety of applications, among which: analysis of RNA [144], [44] gene expression data analysis [157], medical imaging [160], EEG data analysis [64], vegetation classification [145], regionalisation using spatial contiguity constraints [38], [80], [102], [128], text and document clustering [169], [135], [39], [148], information retrieval [177], object and face clustering in video [159], [94], [40], [101], [164], [24], tracking of moving objects using radar sensors [120], time series clustering [83], [106], tourism [36], financial analysis [82], [180], defect prediction [181], [108], cyber security [161], [91], [79], and malware clustering [65].

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