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→ observations (documents) within clusters should be as similar as possible, observations (documents) in different clusters should be as different as possible.

k-means on Commons Roll Calls

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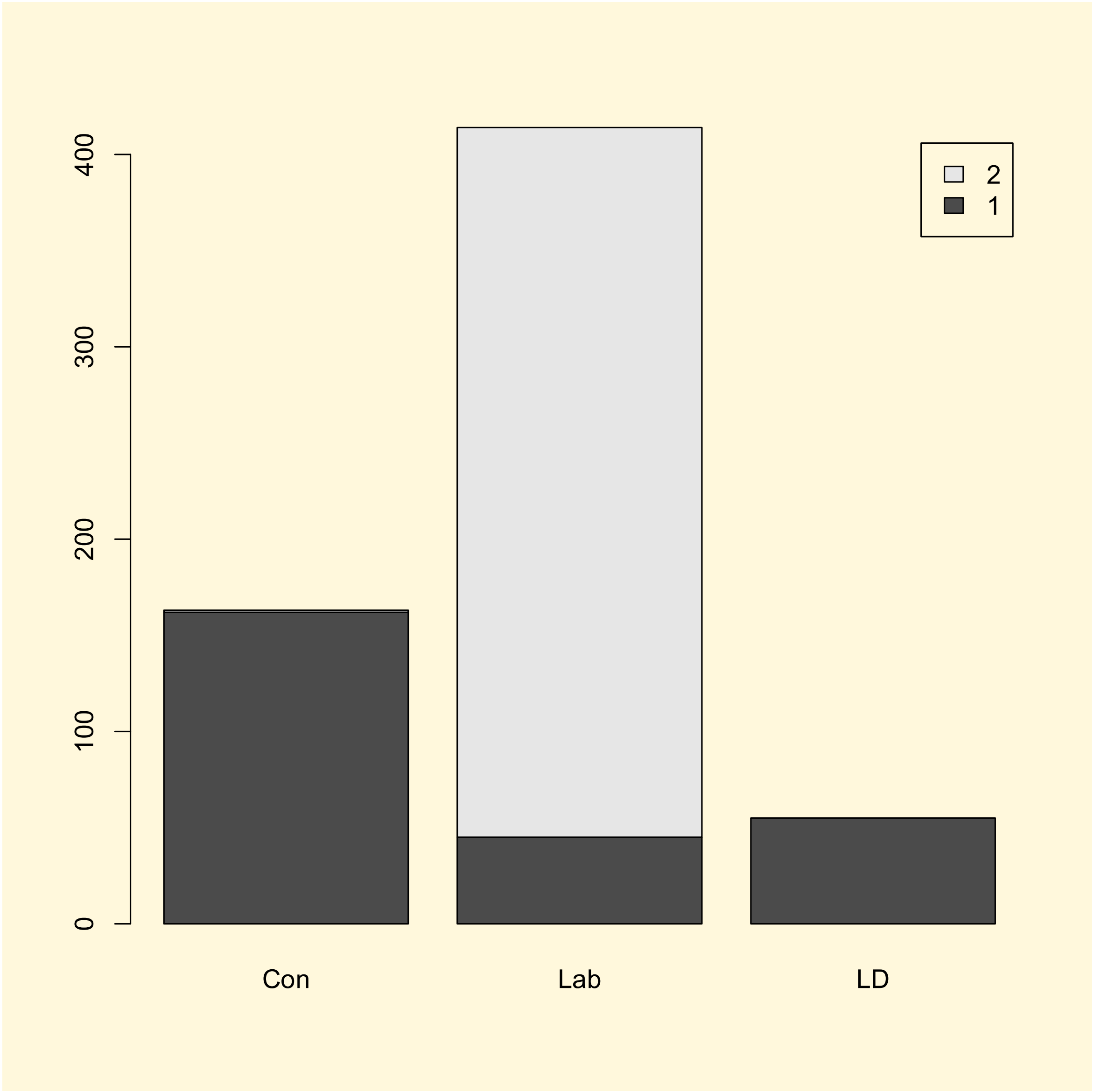

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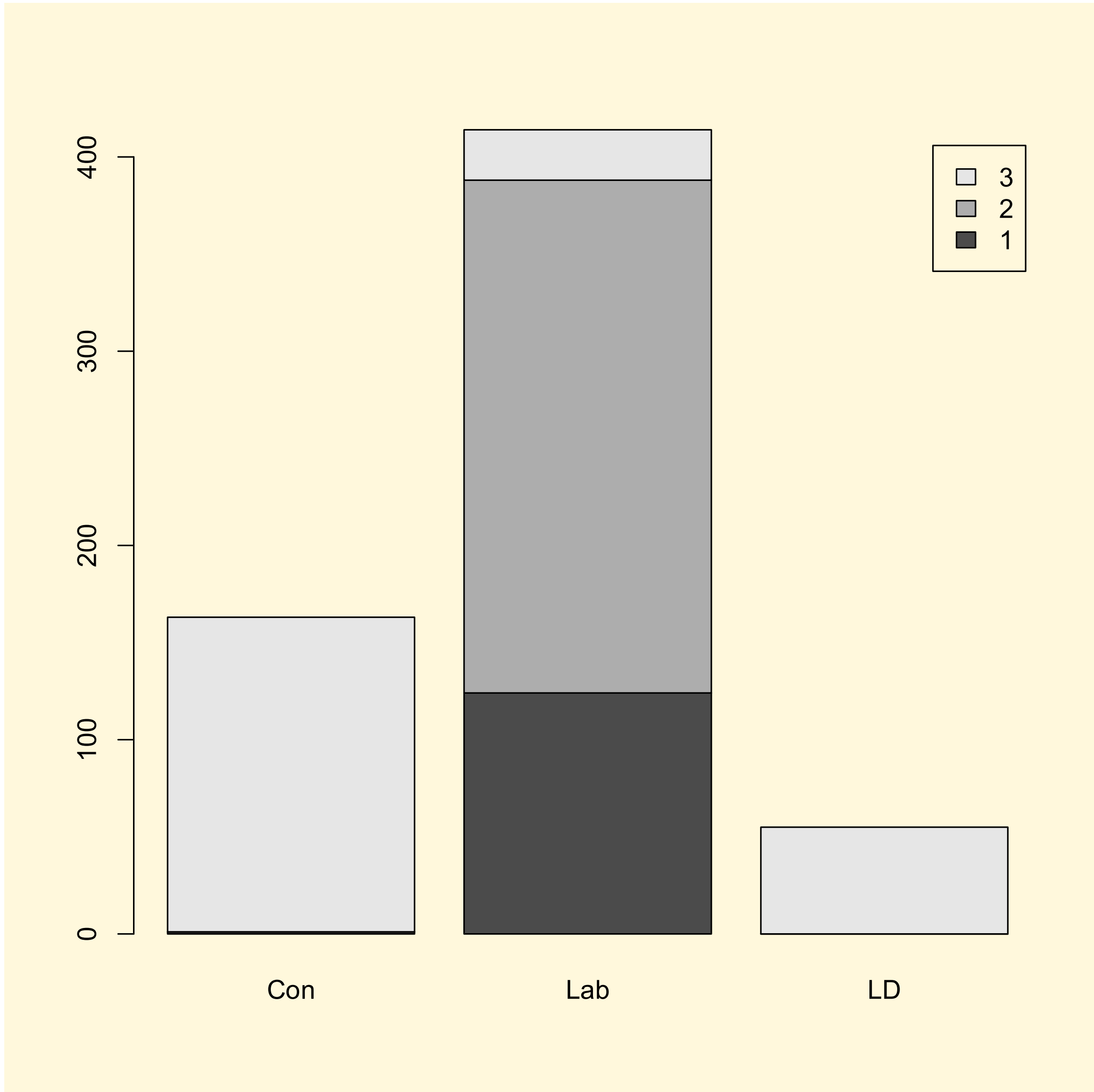

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Or Divisive/top down in sense that everything starts in same cluster and then splits are performed (typically on one feature) to form clusters.

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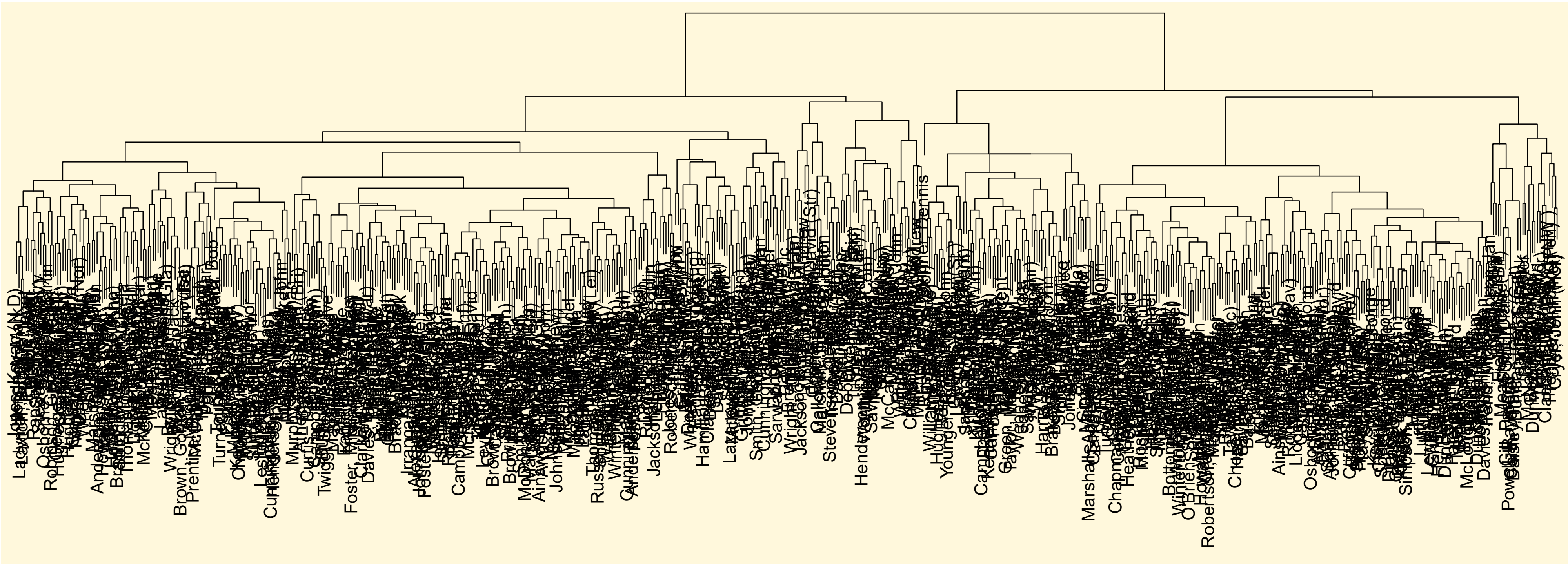

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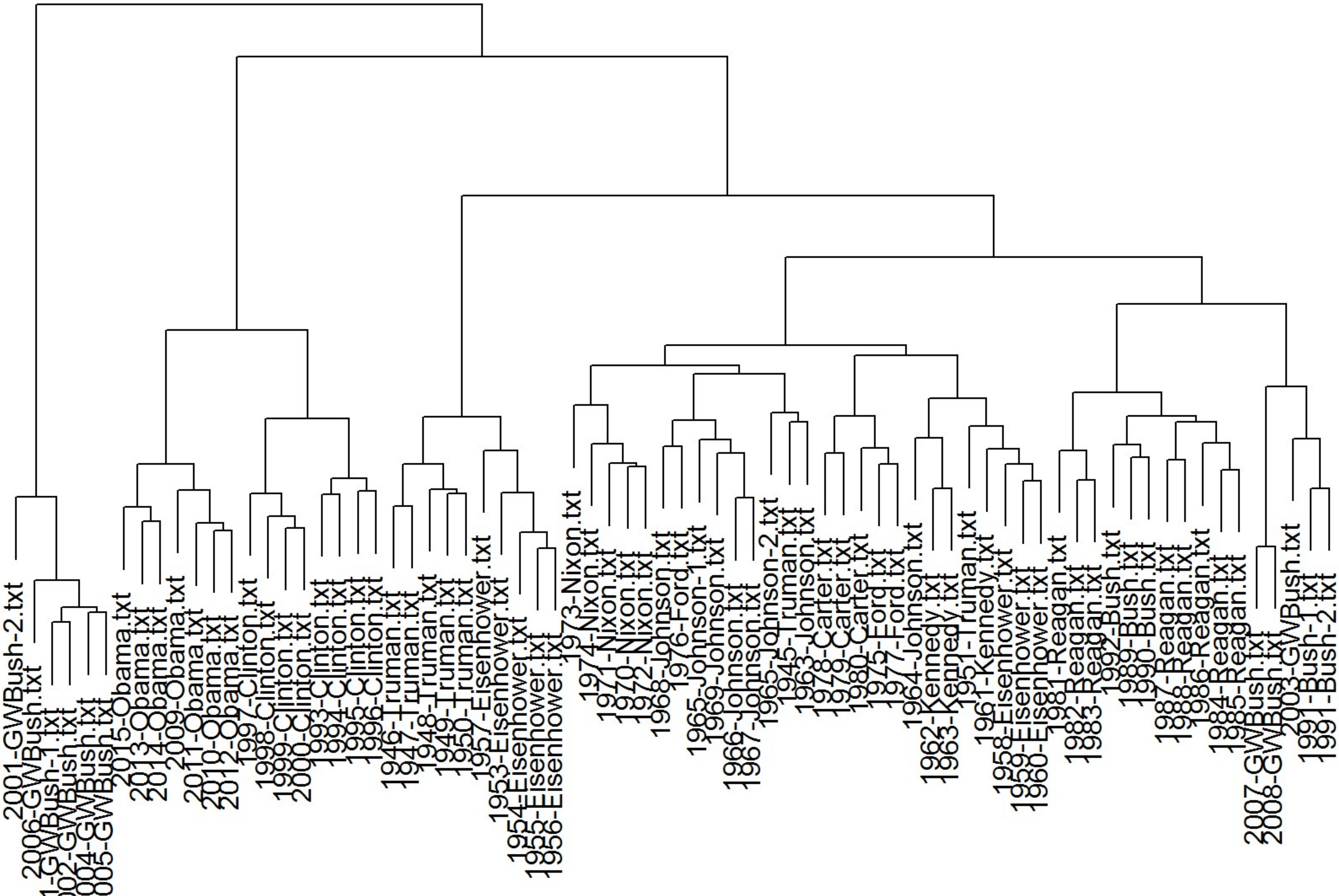

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Plus simultaneously allow users to select combinations of clusterings that look ‘useful’.

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6. visualize for users.

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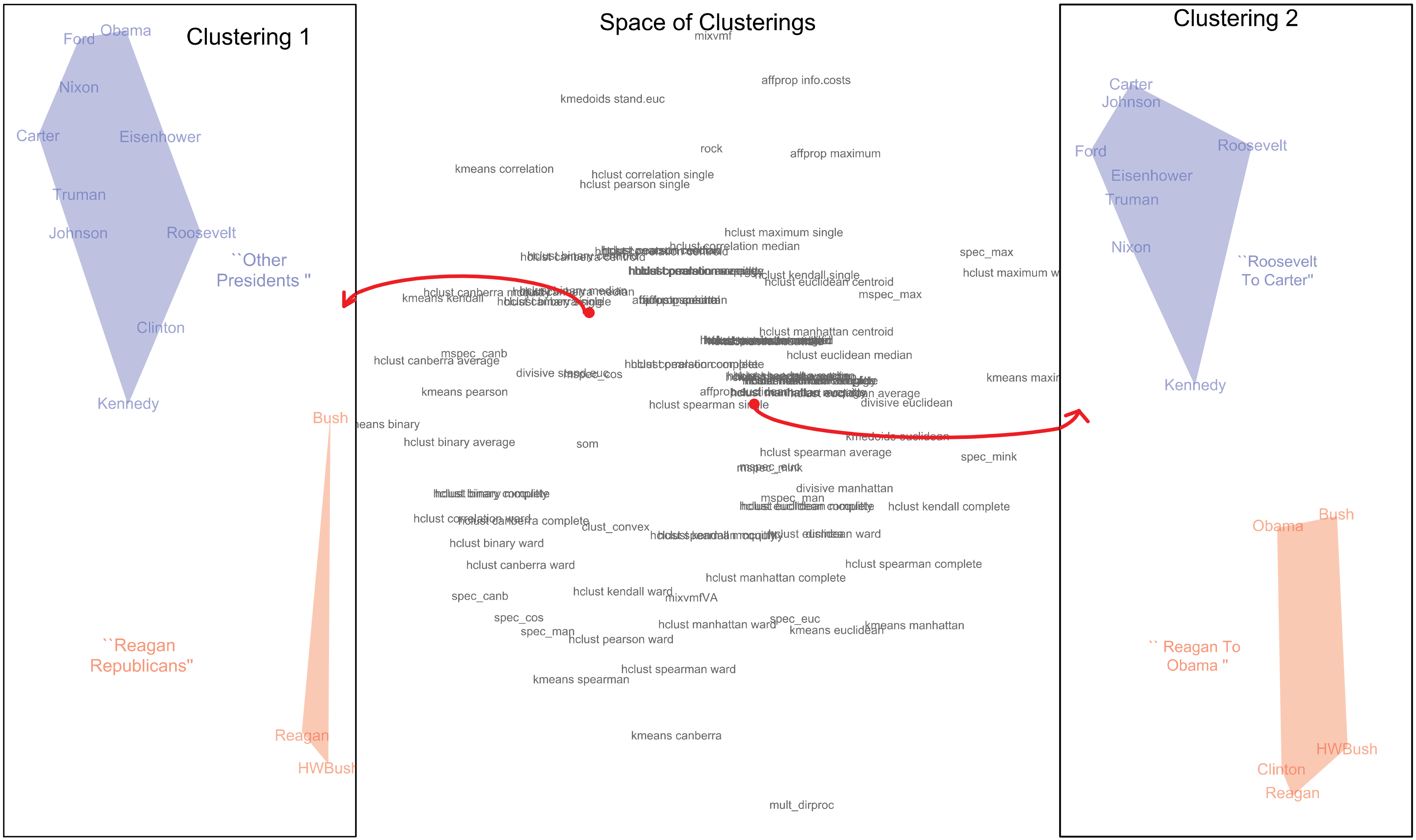

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2. Discovery Quality: show scholars the cluster space and see if it improves their understanding of own data

Discovery of Partisan Taunting in Press Releases

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