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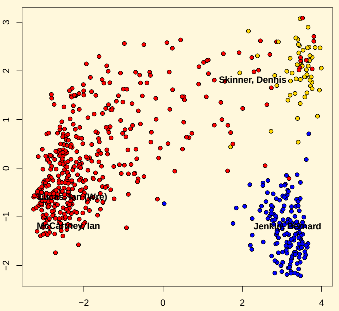

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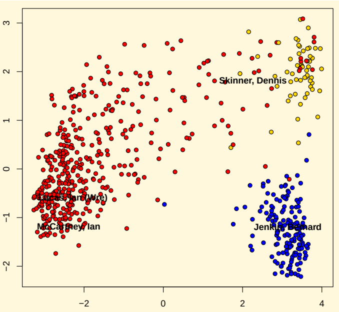

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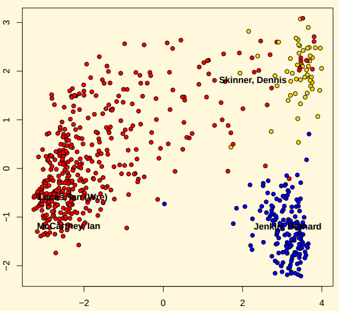

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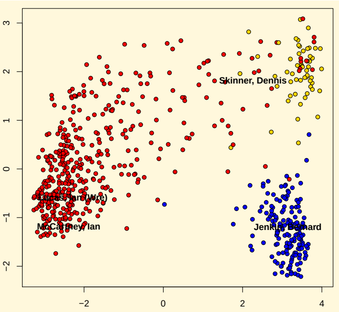

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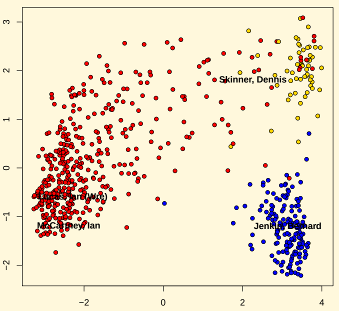

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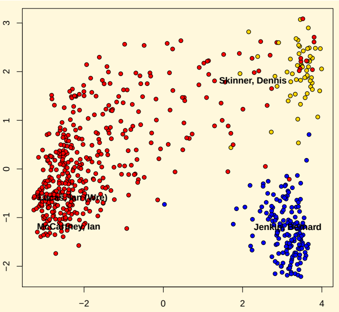

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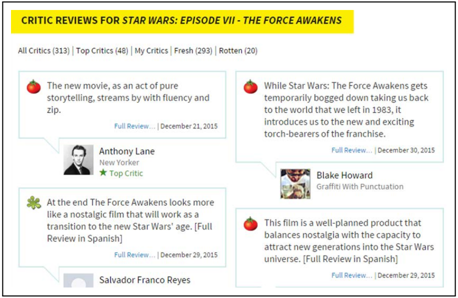

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$\rightarrow$ just add up the number of times the words appear and multiply by the score (normalizing by doc dictionary presence)

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crisis *wasting*

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