Where Are We?

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The Realm of
MIDDLE EARTH
Miles
50 100 150 200
N
The Lost Realm of
ARNOR
ERIADOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Last Bridge
Bree
East-West Road
South Downs
CARDOLAN
THE SHIRE
Sarn Ford
Hobbiton
Nenuial Lake Evendim
North Downs
ERED LUIN
LINDON
Forlindon
Gulf of Lhûn
Grey Havens
Tower Hills
Harlond
Harlindon
Blue Mountains
Baranduin
MINHIRIATH
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
Gwathlo (Greyflood)
ENEDWAITH
Lond Daer
Dunland
Isengard
North-South Road
Fords of Isen
Angren (Isen)
Adorn
Helm's Deep
WESTFOLD
FANGORN
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)

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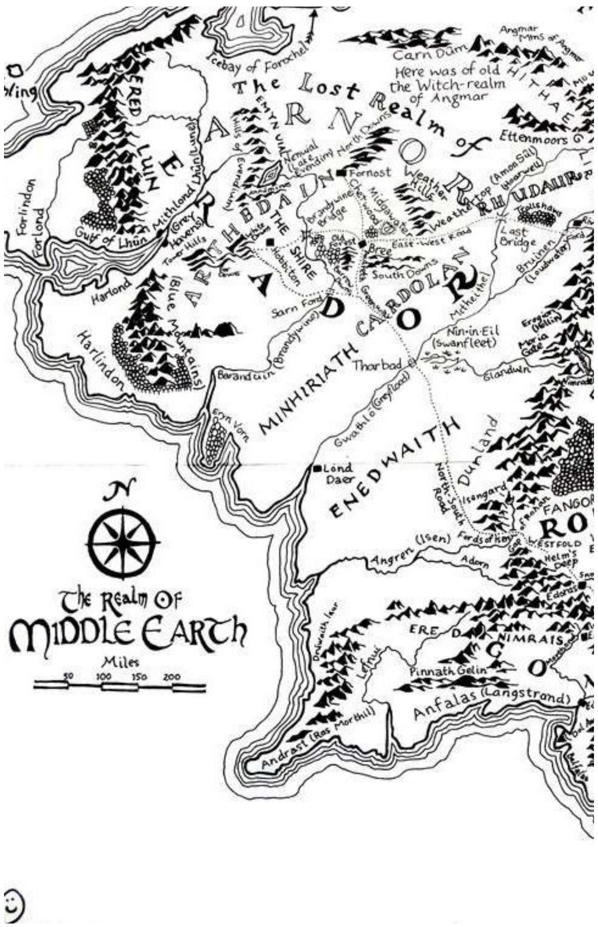

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cover some fundamental techniques for accessing that structure

and demonstrate challenges that emerge in interpreting the results.

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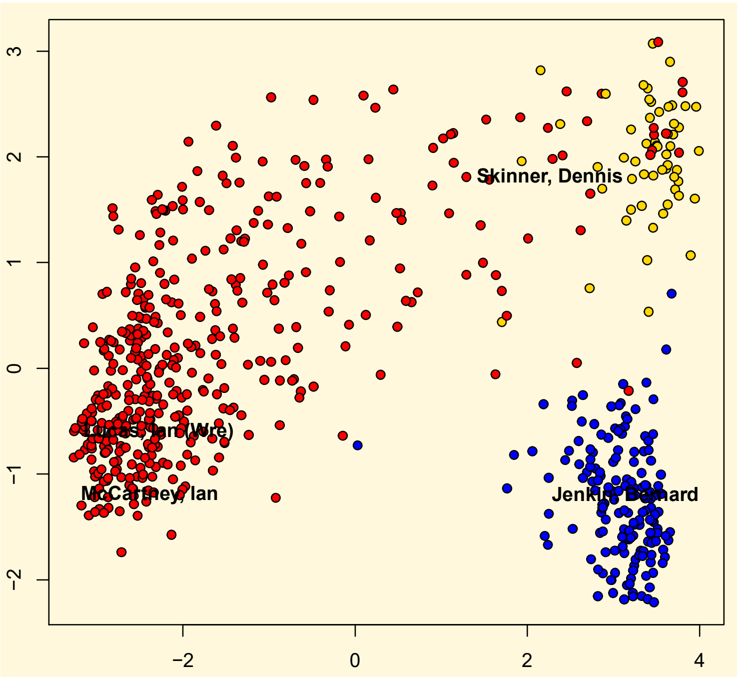

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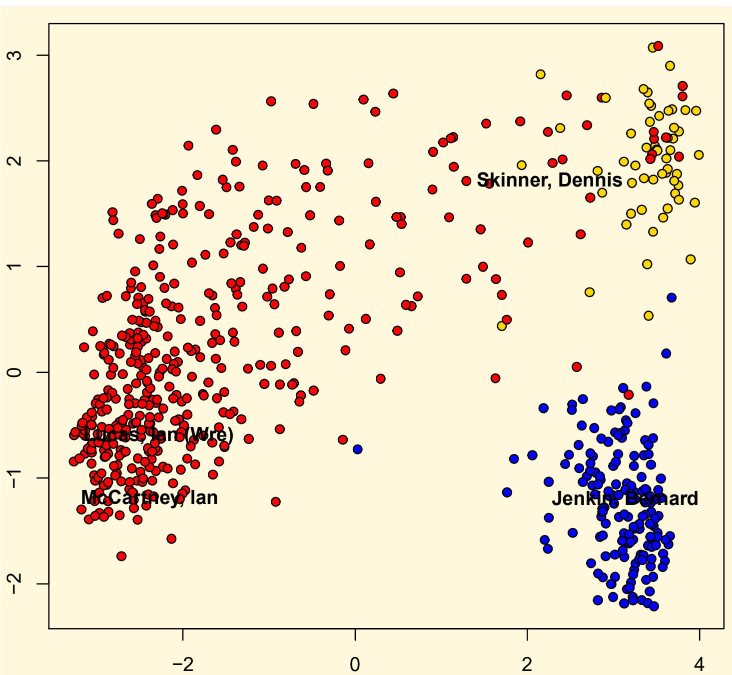

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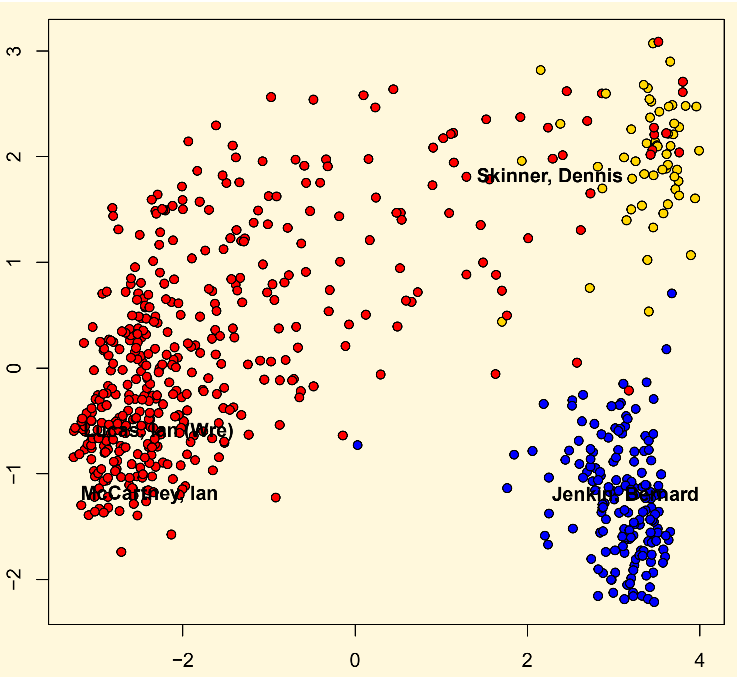

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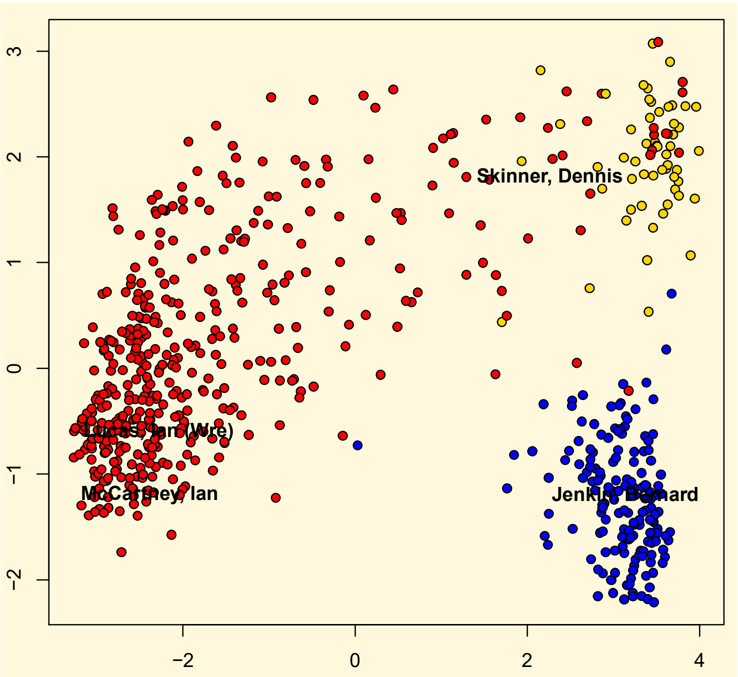

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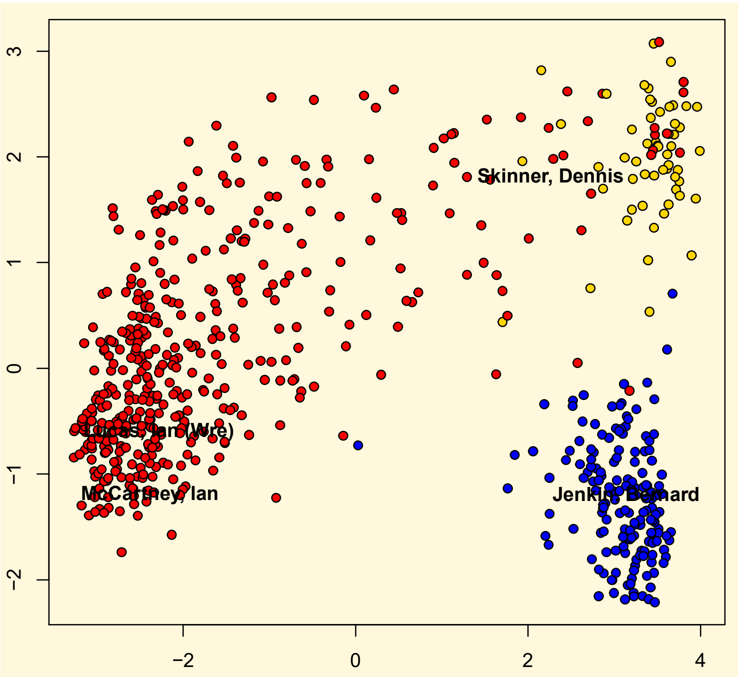

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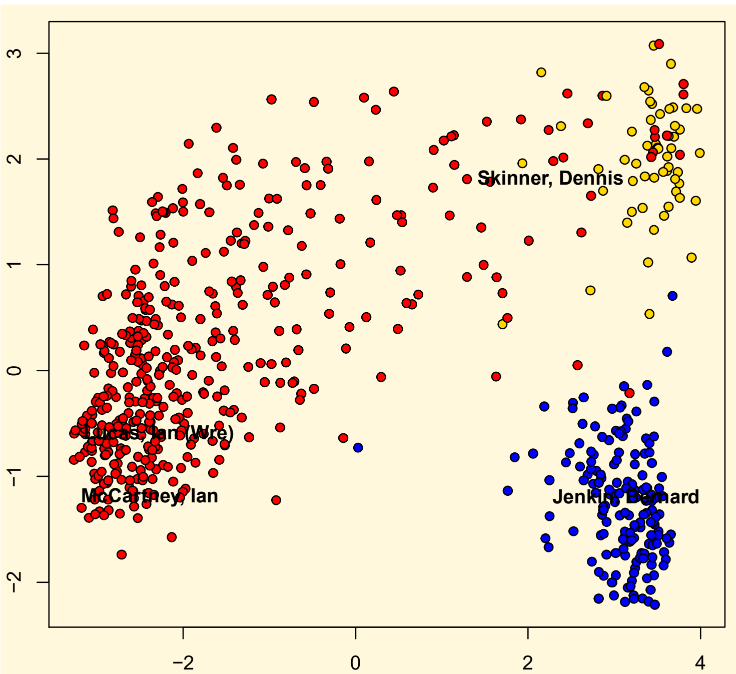

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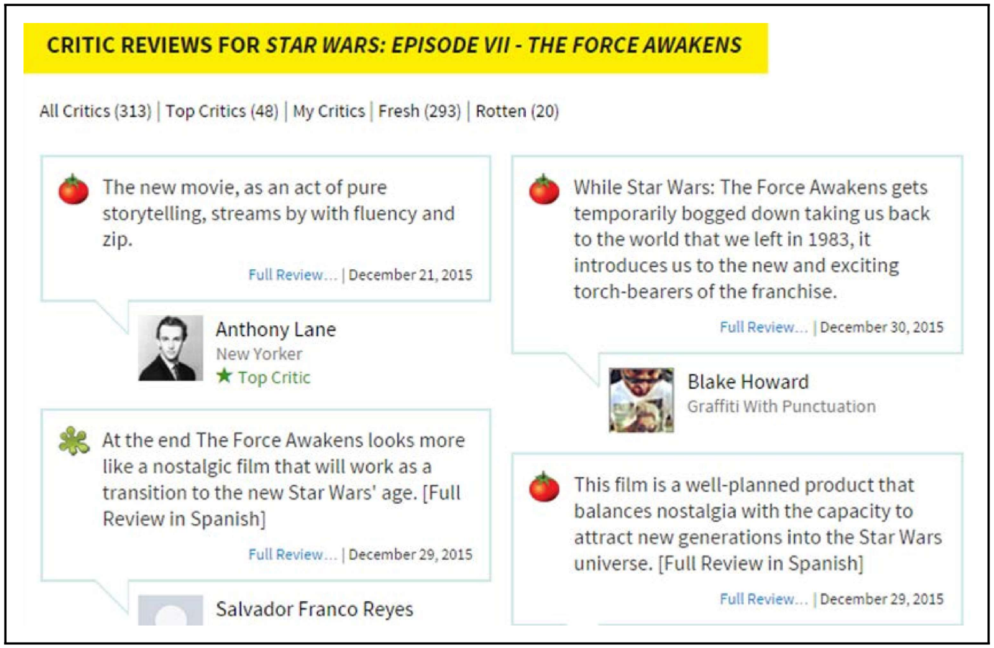
CRITIC REVIEWS FOR *STAR WARS: EPISODE VII - THE FORCE AWAKENS*

All Critics (313) | Top Critics (48) | My Critics | Fresh (293) | Rotten (20)

The new movie, as an act of pure storytelling, streams by with fluency and zip.
Full Review... | December 21, 2015
Anthony Lane
New Yorker
★ Top Critic

While Star Wars: The Force Awakens gets temporarily bogged down taking us back to the world that we left in 1983, it introduces us to the new and exciting torch-bearers of the franchise.
Full Review... | December 30, 2015
Blake Howard
Graffiti With Punctuation

At the end The Force Awakens looks more like a nostalgic film that will work as a transition to the new Star Wars' age. [Full Review in Spanish]
Full Review... | December 29, 2015
Salvador Franco Reyes

This film is a well-planned product that balances nostalgia with the capacity to attract new generations into the Star Wars universe. [Full Review in Spanish]
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(not "what is the recall/precision/accuracy?")

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Name	Party	Vote 1	Vote 2	Vote 3	
Ainsworth, Peter (E S)	Con	NA	1	NA	...
Alexander, Douglas	Lab	NA	0	0	...
Allan, Richard	LD	1	0	1	...
Allen, Graham	Lab	0	0	0	...
Amess, David	Con	1	1	NA	...
					$\ddots$

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Name	Party	'cost'	'spend'	'tax'	
Ainsworth, Peter (E S)	Con	0.00	0.01	0.30	...
Alexander, Douglas	Lab	0.32	0.20	0.86	...
Allan, Richard	LD	0.99	0.82	0.61	...
Allen, Graham	Lab	0.52	0.86	0.34	...
Amess, David	Con	0.07	0.34	0.33	...
					$\ddots$

PCA: Introduction

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Possibly oldest multivariate technique (Pearson, 1901?)