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		Predicted		
		J	$\neg J$	Total
Actual	J	a TP	b FN	$a+b$
	$\neg J$	c FP	d TN	$c+d$
	Total	$a+c$	$b+d$	N

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1. For such a task, there's probably a trade-off between precision and recall. Explain why.
2. We may be skeptical of using accuracy as a performance indicator in this case. Explain why.

Aside: Sometimes Classifier Performance is <u>Substantively</u> Meaningful

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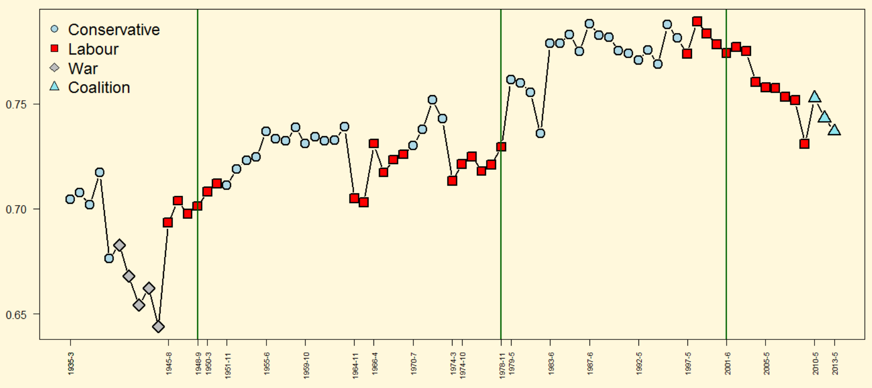

Use machine to classify left (-1) vs right ($+1$) MPs in UK and record classification accuracy.

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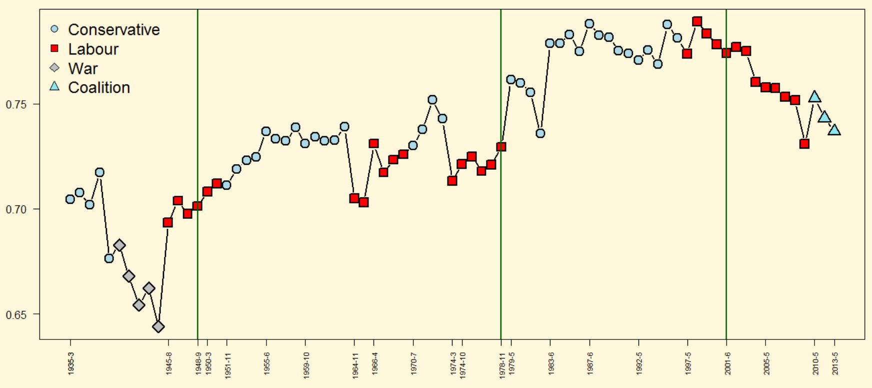

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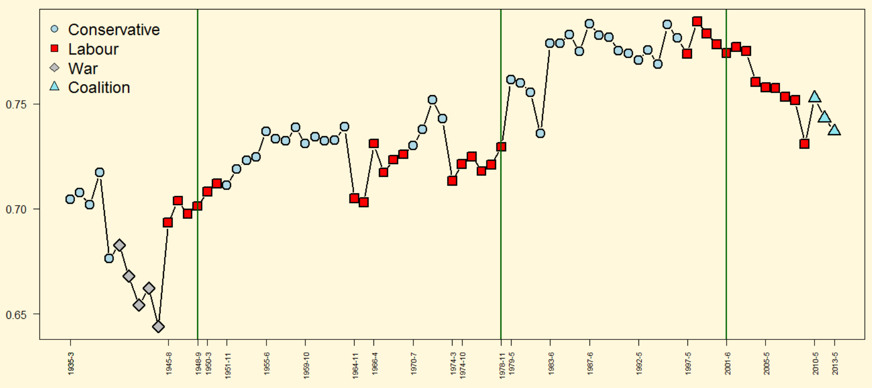

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if we had a large number of 'experts', we could (depending on the size of the problem) have everything as a 'training' set and avoid modeling at all.

Galton and the Wisdom of Crowds

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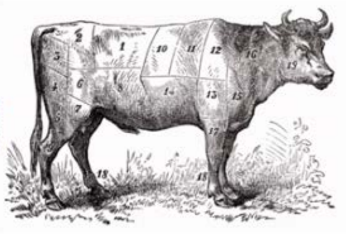

average of 800 guesses = 1,197
actual weight of the ox = 1,198

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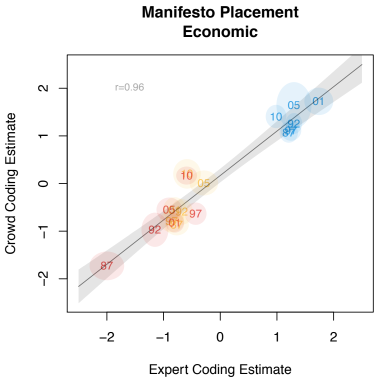

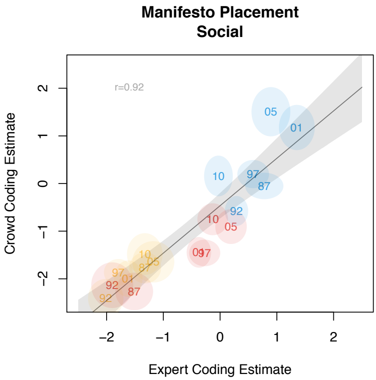

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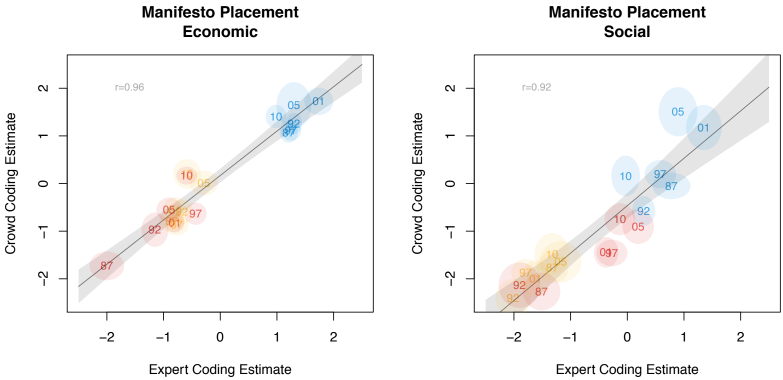

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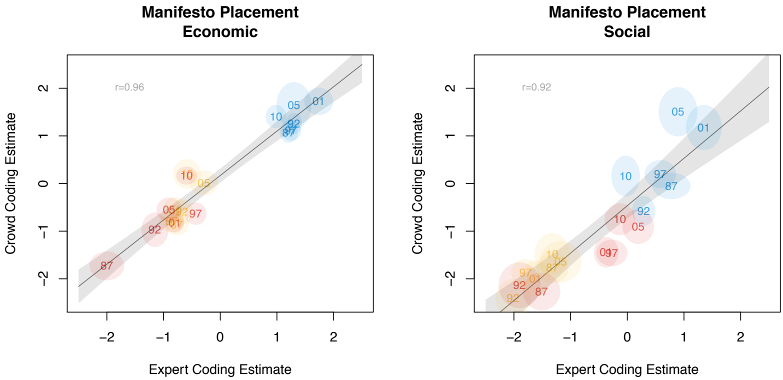

Note that this method allows replication of the data used in an analysis, not just the analysis itself!