Two papers making predictions about the impact of AI on the job market

Alistair Knott

Frey and Osborne (2013)

‘The future of employment: how susceptible are jobs to computerisation?’

- Notorious for predicting 47% of US jobs are ‘highly automatable’.
- Frey and Osborne work at the Oxford Martin School (in the ‘future technology’ programme).
- Frey is an economist, Osborne is in AI (machine learning).

Frey and Osborne (2013)

Section 2: A history of technological revolutions and employment

- 'Since electrification, the story of the twentieth century has been the race between education and technology (Goldin and Katz, 2009).'

Frey and Osborne (2013)

Section 3: The technological revolutions of the 21st century

- ‘Beaudry, et al. (2013) document a decline in the demand for skill over the past decade, even as the supply of workers with higher education has continued to grow. They show that high-skilled workers have moved down the occupational ladder.’

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  - Creative intelligence tasks. (Biologist vs court clerk)
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Section 5: Employment in the 21st century

‘Our model predicts that most workers in transportation and logistics occupations, together with the bulk of office and administrative support workers, and labour in production occupations, are at risk. These findings are consistent with recent technological developments documented in the literature.

More surprisingly, we find that a substantial share of employment in service occupations, where most US job growth has occurred over the past decades (Autor and Dorn, 2013), are highly susceptible to computerisation. (...)

Finally, we provide evidence that that wages and educational attainment exhibit a strong negative relationship with the probability of computerisation.’

Arntz *et al.* (2016)

‘The risk of automation for jobs in OECD countries’

- Comissioned by the OECD
- They’re all economists.

Arntz *et al.* (2016)

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- 'The technical possibility to use machines rather than humans for the provision of certain tasks need not mean that the substitution of humans by machines actually takes place. In many cases, there are legal as well as ethical obstacles that may prevent such a substitution or at least substantially slow down its pace.'

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Their analysis: 'we match the automatibility indicator by Frey and Osborne to the US observations in the PIAAC data based on the occupational codes.'

Arntz *et al.* (2016)

Results: only 9% of OECD jobs are automatable.

- For FO, the occupation ‘bookkeeping/accounting’ is 98% automatable.
  But only 24% of people in this occupation have no ‘group work’ or ‘face-to-face interactions’.
- For FO, the occupation ‘Retail salesperson’ is 92% automatable.
  But only 4% of people in this occupation have no ‘group work’ or ‘face-to-face interactions’.