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A neurocomputational model of developmental trajectories of gifted children under a polygenic model: When are gifted children held back by poor environments?

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ABSTRACT

From the genetic side, giftedness in cognitive development is the result of contribution of many common genetic variants of small effect size, so called polygenicity (Spain et al., 2016). From the environmental side, educationalists have argued for the importance of the environment for sustaining early potential in children, showing that bright poor children are held back in their subsequent development (Feinstein, 2003a). Such correlational data need to be complemented by mechanistic models showing how gifted development results from the respective genetic and environmental influences. A neurocomputational model of cognitive development is presented, using artificial neural networks to simulate the development of a population of children. Variability was produced by many small differences in neurocomputational parameters each influenced by multiple artificial genes, instantiating a polygenic model, and by variations in the level of stimulation from the environment. The simulations captured several key empirical phenomena, including the non-linearity of developmental trajectories, asymmetries in the characteristics of the upper and lower tails of the population distribution, and the potential of poor environments to hold back bright children. At a computational level, 'gifted' networks tended to have higher capacity, higher plasticity, less noisy neural processing, a lower impact of regressive events, and a richer environment. However, individual instances presented heterogeneous contributions of these neurocomputational factors, suggesting giftedness has diverse causes.

Introduction

The causes of giftedness in cognitive or physical abilities are complex, involving both genetic and environmental contributions (Sternberg & Davidson, 2005). Humans with exceptional abilities may have innate potential, but skills must be developed over time, and an individual requires a combination of ambition, opportunity and a willingness to work in order to realise their potential; in this sense, Wai (2014) described experts as *born then made*. Moreover, genetic and environmental factors may be correlated. For example, parents may identify an indication of talent in their children and encourage the talent to flourish through providing opportunities and resources (Ericsson, Nandagopal, & Roring, 2005). Talented children may themselves seek out the environments and activities that will foster development of their abilities (Ericsson, 2014).

Recent work in behavioural genetics has focused on genetic contributions to giftedness. Evidence from twin studies in several countries suggested a genetic contribution to cognitive performance in the high range (Haworth et al., 2009). In these data, genetic influences explained 50% of the variance in those performing in the top 15% of population distributions. Molecular genetics using genome wide association (GWA) analyses suggest that the causes of low performance in the bottom tail of the distribution and high performance in the upper tail may be different, at least for intelligence. Spain et al. (2016) found that while the bottom tail was associated with increased incidence of genetic mutations (rare alleles), the upper tail had, if anything, a reduced frequency of rare alleles. The upper tail appears to be driven by the same genetic influences that operate throughout the rest of the population distribution, with the discontinuity at the lower extreme being the sole exception (Shakeshaft et al., 2015). The wider picture is that genetic contributions to intelligence stem from many common genetic variations each of small effect, known as the 'polygenic' model

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(Plomin & Deary, 2015); rare functional variants are more often detrimental than beneficial to intelligence.

Lykken (2006); see also Simonton, 1999, Simonton, 2005 argued that the genetic contributions to giftedness were multiplicative, such that if any of a set of genetic variants was absent, this would negate a gifted outcome – the so-called *emergenic* model. However, twin studies have suggested the genetic contributions to giftedness for intelligence appear to be additive in effect rather than dominant (that is, identical twins are not more than twice as similar as fraternal twins). Plomin and Deary (2015) concluded that twin studies of intelligence consistently find the genetic influence to be largely, if not entirely, additive for high intelligence as well as the entire distribution of intelligence (see also Plomin & Haworth, 2009) – although small or rare non-additive effects cannot be definitely ruled out due to the lack of statistical power to detect them. In sum, then, genetic influence on cognitive ability appears to involve many genes each contributing small effects; these contributions are additive; and for high ability, these genes are common variants. The innately gifted individual has been lucky enough to inherit cognitively beneficial versions of many genes.

Behaviour genetics generates these insights from correlational analyses. However, genetic effects must ultimately unpack in causal properties of the brain and body. With respect to the former, such properties may be construed in terms of neural mechanisms and neurocomputational properties. In these terms, gifted performance is the result of many small advantageous aspects of neurocomputation, potentially across multiple systems, and their contribution to the development and maintenance of cognitive and physical abilities.

A separate literature in educational achievement has focused on environmental influences on the development of children with different levels of ability. Taking a long-term perspective, this literature highlights the role of socio-economic status (SES) in either fostering or holding back early potential. In a seminal paper, Feinstein (2003a) presented an analysis of longitudinal data, grouping children by cognitive ability at 22 months, and then following these children through to 10 years of age. Children from low SES families (where SES was defined by parental education level) did not, on average, 'overcome the hurdle of lower initial attainment, combined with continued low input' (Feinstein, 2003b, p. 30). But notably, social inequalities also appeared to dominate the early positive signs of academic ability for most of those low SES children who did well early on. The message that policymakers took from these data was that bright children from poorer families tend to fall back relative to more advantaged peers who have not performed as well (Feinstein, 2015).

This pattern is depicted in later Fig. 1(a) replotted from Feinstein (2003b). It shows the population rank order of children classified by ability in the top quartile and bottom quartile on cognitive tests at age 22 months, and then those groups split into high SES (top 24% of population) and low SES (bottom 13%). The top quartile ability / low SES group shows a declining mean rank across age, while the bottom quartile ability / high SES group shows an increasing mean rank. There has been some subsequent debate about the shape of this function: whether the rank trajectories of these two groups really cross, and whether some of the pattern is explained by regression to the mean of initially extreme scores, due to measurement error in the repeated cognitive testing (Jerrim & Vignoles, 2013). However, there is consensus on the main finding: the benefits of good early development can be substantially eroded by social class effects.

Nevertheless, as with data from genetic studies, investigations of environmental influences on the development of children with high ability remain correlational. They stand in need of a mechanistic account that identifies how the proxy of SES translates into actual influences that shape the development of cognitive abilities in children.

In this paper, we use neurocomputational modelling of cognitive development to focus on the mechanistic basis of genetic and environmental influences on high ability. Considering development across a whole population, artificial neural network models are employed to integrate data across levels of description: from the genetic level in terms of influences on neurocomputation; from the environmental level in terms of influences on the level of stimulation children receive from the environment; and from the behavioural level, in terms of scores on cognitive tests.

In previous work, we have shown how modelling cognitive development using populations of artificial neural networks can provide a unified framework to consider individual differences within a developmental framework and integrate across levels of description (Thomas, Forrester, & Ronald, 2016). We have shown that observed SES effects on language development can be simulated by modulating the richness of linguistic experience received by children in families of different SES levels (Thomas, Forrester, & Ronald, 2013). Moreover, this model simulated the asymmetric quality of high and low tails observed in genetic studies: SES predicted whether simulated individuals would fall in the top 10% of the population, but not if they would fall in the bottom 10%. This is because there are many ways to fail but few to succeed: therefore the predictive power of a single factor is reduced for poor outcomes. This novel prediction was subsequently confirmed by a re-analysis of empirical data collected by Bishop (2005). We also investigated the causes of delayed development in this model framework, following the trajectories of simulated children who exhibited early delay (Thomas & Knowland, 2014). Of these individuals, two thirds subsequently resolved to the normal range later in development. This replicates a pattern observed in the empirical literature (e.g., Dale, Price, Bishop, & Plomin, 2003). The model once more produced a novel prediction: that SES should predict variance in the final language ability level of children whose early delay resolved, but not in those where the delay persisted. Once more, this prediction was confirmed by the empirical data (Bishop, 2005).

The modelling framework has therefore demonstrated its initial adequacy to investigate the mechanistic basis of individual differences. In the current work, the Thomas et al. (2013) model is employed to address the developmental trajectories of 'gifted' simulated children falling in the upper tail of early performance. Our key questions are as follows: (1) For those simulated individuals showing high early ability, what are the neurocomputational and environmental factors that predict the long-term outcome of developmental trajectories? (2) In a mechanistic model of experience-dependent development, where all sources of variation are specified and there is no measurement error, can the Feinstein graph be replicated, with the population rank order of gifted individuals from lower SES backgrounds subsequently declining across development? (3) If such a decline is observed, must the computational causes of the changes in rank be entirely environmental, as proposed? (4) If changes in population rank are not entirely environmental, can the risk of subsequent decline be predicted from behavioural measures taken when early giftedness is first recognised?

1. Computational modelling

1.1. Simulation details

1.1.1. Base model

The base model was drawn from the field of language development, and specifically the acquisition of the English past tense within inflectional morphology. The model is used here to stand for more general models of cognitive development utilised in cognitive modelling (see e.g., Mareschal & Thomas, 2007). The model employed an artificial neural network architecture.

A backpropagation network was used to learn to output the past-tense form of a verb from an input vector that combined a phonological representation of the verb stem and lexical-semantic information (Joanisse & Seidenberg, 1999). The architecture is shown in Fig. 2.

The training set was the "phone" vocabulary from Plunkett and Marchman (1991). This comprised an artificial language set constructed to reflect many of the important structural features of English