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Modeling Socioeconomic Status Effects on Language Development

Michael S. C. Thomas, Neil A. Forrester, and Angelica Ronald
Birkbeck, University of London

Socioeconomic status (SES) is an important environmental predictor of language and cognitive development, but the causal pathways by which it operates are unclear. We used a computational model of development to explore the adequacy of manipulations of environmental information to simulate SES effects in English past-tense acquisition, in a data set provided by Bishop (2005). To our knowledge, this is the first application of computational models of development to SES. The simulations addressed 3 new challenges: (a) to combine models of development and individual differences in a single framework, (b) to expand modeling to the population level, and (c) to implement both environmental and genetic/intrinsic sources of individual differences. The model succeeded in capturing the qualitative patterns of regularity effects in both population performance and the predictive power of SES that were observed in the empirical data. The model suggested that the empirical data are best captured by relatively wider variation in learning abilities and relatively narrow variation in (and good quality of) environmental information. There were shortcomings in the model's quantitative fit, which are discussed. The model made several novel predictions, with respect to the influence of SES on delay versus giftedness, the change of SES effects over development, and the influence of SES on children of different ability levels (gene–environment interactions). The first of these predictions was that SES should reliably predict gifted performance in children but not delayed performance, and the prediction was supported by the Bishop data set. Finally, the model demonstrated limits on the inferences that can be drawn about developmental mechanisms on the basis of data from individual differences.

Keywords: socioeconomic status, language development, individual differences, artificial neural networks, resilience

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In this article, we use population-level computational modeling to investigate the mechanisms by which socioeconomic status (SES) influences language development. SES is a well-known environmental measure that predicts significant individual differences in cognitive and language development, and even some measures of brain function, such as hemispheric specialization (see Hackman & Farah, 2009, for review). SES is usually assessed via parental education and income levels, and the measure is thus only a proxy for the relevant causal mechanisms operating on cognitive development. The causal pathways by which SES affects development are challenging to identify: Many environmental factors covary with SES; more than one factor may affect development at any one time; the factors may be different for different aspects of cognition; and the relevant factors may change across development.

Hackman, Farah, and Meaney (2010) identified three classes of mechanism by which SES effects on brain and cognition may operate. The first class is *prenatal influences*. Low SES is associated with increased likelihood of premature birth and impaired fetal growth, higher levels of stress, higher infection rates, and poor nutrition during pregnancy. These factors may affect early brain development. The second class is *parental care*. Low SES can impact on factors such as discipline, parent–child verbal communication and parental sensitivity to the needs of the child. Quality of parenting may also impact on neurodevelopment. The third class is the level of *cognitive stimulation* available in the home environment, including factors such as the availability of books, computers, trips, and parental communication.

SES has been found to have a differential impact across different areas of cognition. In one study with 12-year-olds, Farah et al. (2006) observed the largest SES effects on language measures (30% of the variance explained), memory (17%), and working memory (10%), with smaller, nonsignificant effects reported on cognitive control (6%), spatial cognition (6%), visual cognition (3%), and reward processing (0.3%). Longitu-

Michael S. C. Thomas, Neil A. Forrester, and Angelica Ronald, Developmental Neurocognition Lab, Centre for Brain and Cognitive Development, Department of Psychological Sciences, Birkbeck, University of London, London, England.

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Correspondence concerning this article should be addressed to Michael S. C. Thomas, Developmental Neurocognition Lab, Centre for Brain and Cognitive Development, Department of Psychological Sciences, Birkbeck, University of London, Malet Street, Bloomsbury, London WC1E 7HX, England. E-mail: m.thomas@bbk.ac.uk

dinal data and twin data suggest that environmental effects may operate on different abilities via separate causal pathways. Farah et al. (2008) found that parental care predicted later variability on memory tasks (11% of the variance) but not on language tasks, whereas cognitive stimulation predicted later variability on language tasks (50% of the variance) but not on memory tasks. In a twin design, Stromswold (2006) assessed the heritability of abilities when the sample was split by different environmental risk factors. For the twin sample, perinatal environmental risk factors (gestational age) depressed the heritability of language, motor, and social skills but not cognitive skills, whereas postnatal risk factors (mother's education and family income) showed the reverse pattern.

Turning to language development, a similar differentiation of SES effects has been observed within language skills themselves. Greater effects are observed on vocabulary and phonology, and lesser effects on syntax. For example, Noble, Norman, and Farah (2005) found that SES predicted 24% of the variance in receptive vocabulary skills, 24% of the variance in phonological awareness, but only 5% of the variance in receptive grammar skills. Within grammar, one study reported early and persistent SES effects on the emergence of productive syntax in children between 22 and 42 months of age, but only for complex sentences (explaining around 15% of the variance), not for simple sentences (Vasilyeva, Waterfall, & Huttenlocher, 2008).

Researchers in language development have tended to focus on the role of input in modulating SES effects, that is, postnatal influences linked to environmental stimulation. This focus has arisen for three reasons. The first reason is that large differences have been observed in the nature of the language addressed to children at different levels of SES. For example, Hart and Risley (1995) followed children in professional/managerial families, working-class families, and families living on benefits, between the ages of 8 months and 3 years, recording all language produced by the child or available around the child for 1 hr per month. The most salient difference was the quantity of language spoken to the child. Professional families addressed 2,100 words to their child in the average hour compared to 600 in the welfare families. Higher SES was also associated with a greater incidence of affirmative feedback and lower incidence of prohibitions. Lastly, parents who used more words tended to use a greater variety of words and use them in longer sentences (Hart & Risley, 1992).

The second reason for focusing on input is that once differences in language input have been controlled for, several studies have reported that the predictive effect of SES disappears. Huttenlocher, Vasilyeva, Cymerman, and Levine (2002) and Huttenlocher, Waterfall, Vasilyeva, Vevea, and Hedges (2010) both reported a number of correlations between measures of parental language (complexity of sentences, diversity of words or sentences) and children's language skills, as well as reliable effects of SES. The SES effects either disappeared or were much reduced when differences in parental input were controlled for. The implication was that SES effects were mediated partially or fully by language input.

In principle, correlations between parental speech and child language acquisition could be explained by their biological relatedness. The third reason is that studies have also been able to implicate language input as playing a causal role. For example, Huttenlocher et al. (2002) demonstrated that a measure of the sentence complexity of (biologically unrelated) classroom teachers' language predicted the improvement in their children's sentence comprehension over the school year (explaining 18% of the variance), but not improvement in math skills (for related work, see also Klibanoff, Levine, Huttenlocher, Vasilyeva, & Hedges, 2006; Vasilyeva, Huttenlocher, & Waterfall, 2006). Huttenlocher et al. (2010) used longitudinal cross-lagged analyses to inform the directionality of the relationships they observed. For syntax, the only reliable relationships were between the early input from the parent and the later ability of the child, suggesting a causal flow from parent to child.

Studies of SES have in the main addressed the sources of individual differences in the trajectories of language development. However, these data have also been used to draw inferences about the nature of language development itself. For example, Rice, Wexler, and Hershberger (1998) compared developmental trajectories of English past-tense acquisition longitudinally in children with specific language impairment and typically developing children over a 3-year period. They found that SES (as measured by maternal education) was a nonsignificant predictor (less than 1% of the variance) of differences between children's trajectories over time. On the basis of the failure of measured environmental variables to explain differences between individuals, Rice et al. inferred that the growth in ability (development) was explained by *maturational mechanisms*, where changes in behavior over time are due to the aging process rather than experience-dependent learning; and that the difference between typically developing children and those with developmental language impairment lies in genetic differences in the specification of the timing of linguistic properties. SES effects, then, are held by some researchers to have implications for our understanding of how all children acquire language.

Computational Modeling

One complementary methodology to evaluate causal theories is computational modeling. Implemented models of the developmental process can demonstrate the sufficiency of causal accounts to explain observed data. Computational models have been extensively applied to investigating the mechanisms of language development, including simulating early phonological development, lexical segmentation, vocabulary development, the acquisition of pronouns, the development of inflectional morphology, syntax comprehension, syntax production, metaphor comprehension, and reading (for reviews, see Chater & Christiansen, 2008; Mareschal & Thomas, 2007). To our knowledge, no models have sought to simulate individual differences that stem from variations in the SES of the families in which children are raised. There are several challenges to be addressed in applying models in this way.

The first challenge is the requirement to stipulate the way or ways in which SES influences the developmental process. Computational models of development involve the interaction of a learning system with a training environment. Usually, models are applied to capturing the developmental profile of the average child, less frequently to individual differences. Some consideration has been given to altering the computational properties of the learning system to explain individual differences in intelligence (e.g., Garlick, 2002; Richardson, Baughman, Forrester, & Thomas, 2006; Richardson, Forrester, Baughman, & Thomas, 2006) or the deficits observed in developmental disorders (e.g., Thomas & Karmiloff-Smith, 2003a, 2003b). The construction of a computational model of SES effects necessitates committing to a particular implementation of environmental variation and then evaluating its adequacy in capturing observed behavioral data. Indeed, one of the virtues of modeling is the theoretical clarity required by such commitments. Two avenues of implementing SES effects are apparent. The first avenue is to implement SES as a manipulation of the language information available to the child. SES might alter the quality or quantity of that information; or it might alter the motivation of the child to engage with the information available, perhaps through differences in reward and punishment—in effect, this would modulate the subjective information that the child actually exploits from that objectively available in the environment. The second avenue is to implement SES as a manipulation of the computational properties of the learning system. This would implement the idea the environment may operate via biological influences on brain function, for example, via perinatal effects on neural development or via factors such as diet and stress during early child development. These factors would serve to alter the computational properties of the learning system. In the following, for the most part we concentrate on evaluating the adequacy of manipulating the input as the pathway through which SES influences language development.

The second challenge in modeling SES effects is that such effects are not a property of the individual but of a population. Moreover, it is widely held that individual differences of a genetic origin are responsible for a significant proportion of individual differences in behavior, including language development (Plomin, DeFries, McClearn, & McGuffin, 2008; Smith, 2007; Stromswold, 2006). Therefore it is necessary to simulate a large population of individuals, and implement both environmental and genetic contributions to individual differences. We expand on these challenges in the modeling section, where we also establish our criteria for success or failure of the simulations.

SES Effects and the Acquisition of the English Past Tense

The simulations we present focus on the target domain of English past-tense acquisition. Although this domain exhibits relatively smaller SES effects compared to vocabulary and phonology, we selected it for four reasons. First, there is an extensive history of modeling past-tense acquisition, so there is some consensus on what the normal model should look like and the key assumptions that generate its behavior. Second, past tense is a theoretically interesting domain because of the dimension of regularity: English verbs can form their past tense according to a regular rule, but there exist a set of exceptions. Much theoretical debate has ensued on how the difference between regularity and irregularity is reflected in processing structures (if at all) and the extent to which irregular inflections rely on lexical knowledge. Third, we had a large data set available to us demonstrating SES effects on past-tense acquisition, to serve as a target for our simulations. These data are from 270 six-year-old children, originally published as part of Bishop (2005; see also Bishop, Adams, & Norbury, 2006), although the SES effects were not reported in that work. Notably, as we shall see, SES effects were observed in inflecting both regular and irregular verbs, but more strongly for irregular verbs. Fourth, since we understood the developmental processes operating in the computational model, we were able to evaluate what legitimate inferences could be made about the developmental process based on evidence of SES effects. We begin by describing the target empirical data.

Empirical Data: English Past-Tense Formation

Children's acquisition of tense formation, along with other aspects of inflectional morphology, has been the focus of a great deal of empirical research. In part, this is due to the quasiregular nature of the domain. Past tense comprises a regular rule (add *-ed* to form the past tense; e.g., *talk–talked*), which is readily extended to novel forms (*wug–wugged*), and also a set of irregular past tenses that are exceptions to the rule (*go–went*, *sing–sang*, *hit–hit*). Although the regular–irregular dimension is sometimes presented as a dichotomy, it is better viewed as a continuum, with graduations of similarity between regular and irregular inflection. The investigation of the processing structures necessary to acquire a quasiregular domain has led to an extended debate (Pinker, 1999; Rumelhart & McClelland, 1986; see Thomas & McClelland, 2008, for a review). Some of the key data involve children's greater ease in acquiring the past tense of regular verbs compared to irregular verbs, and the presence of overgeneralization errors, where children mistakenly apply the regular rule to the exception forms (e.g., *thinked*).

Tense acquisition has been considered more widely within the theoretical framework of the optional infinitive stage (Wexler, 1994, 1996). Young children pass through a phase where they sometimes omit grammatical morphemes, such as those marking tense, in contexts where the morphemes are obligatory for grammatical correctness. Where finite inflected forms are expected, children sometimes produce infinitival forms (in English, unmarked verb stems; e.g., *yesterday I talk to my friend*). Wexler suggested that in this phase of acquisition, children regard the infinitive as an optional form of the verb. Notably, in children with specific language impairment, such infinitival forms are observed at ages where typically developing children have ceased to use them. This has led to the proposal that in specific language impairment, there is an extended optional infinitive stage, so that problems in tense marking might be diagnostic of the disorder (Rice, Wexler, & Cleave, 1995). In 2001 Rice and Wexler published a diagnostic test for early grammatical impairment in which tense marking was one of the key aspects of the assessment. The past-tense elicitation subtest assessed accuracy levels in producing regular and irregular past tenses, as well as the level of overgeneralization errors, where the regular rule is mistakenly applied to irregular verbs. Since such overgeneralization errors still represent finite forms (just the wrong one), Rice and Wexler used the three scores to compute a fourth, the proportion of regular and irregular verbs that were produced in the finite form. The finiteness measure was equal to the sum of correct regular, correct irregular, and incorrect overregularized irregular verbs, divided by the total number of regular and irregular verbs attempted. The performance of a group of children on the Rice–Wexler past-tense task forms the target empirical data for the computational simulations.

Bishop (2005) gave the Rice–Wexler past-tense subtest to a population of 442 six-year-old children, for whom SES information was additionally available (Bishop, 2005; Petrill, Pike, Price, & Plomin, 2004). These data were originally collected as part of a twin study and published in composite form (Bishop, 2005). The author kindly made the raw data available to us, including accuracy levels on regular and irregular verbs, overgeneralization error rates, and the computed finiteness measure, along with the SES measure. The Bishop data allowed us to assess the predictive power of SES on two verb types and one error type at one particular age. To our knowledge, they represent the largest data set on SES effects on English past-tense acquisition.

Details of the Rice–Wexler past-tense subtest (Rice & Wexler, 2001), the composition of the sample of 270 typically developing 6-year-olds selected from the Bishop (2005) population, and the SES measure, based on parental education and family income, can be found in the supplemental materials. The original population comprised twin pairs and was oversampled for risk of language delay at age 4. However, children who had a language impairment at age 6 were excluded from the final sample of 270. The implications of both these characteristics of the Bishop population are considered in the supplemental materials.

Table 1 includes the mean and standard deviation for accuracy of production of regular and irregular verbs, the rate of overgeneralization errors, and the composite finiteness measure. An advantage for regular verbs was observed, whereas performance on irregular verbs was fairly poor, with high rates of overgeneralization (regulars > irregulars), $t(269) = 35.76$, $p < .001$. Figure 1 displays scatterplots linking past-tense performance with the SES measure for the four dependent variables. SES predicted regular verb performance at marginal significance and irregular verb performance more robustly; it predicted irregular performance significantly more strongly than regular: regular, $R^2 = .013$, $F(1, 268) = 3.56$, $p = .060$; irregular, $R^2 = .047$, $F(1, 268) = 13.13$, $p < .001$; interaction, $F(1, 268) = 7.46$, $p = .007$, $\eta_p^2 = .027$.[1] One concern with this data set is the large number of children at ceiling on regular verbs, which might account for the reduced predictive power of SES. Figure 2 displays the data removing all children for whom regular verbs were at ceiling but irregulars were not (reduced sample $N = 64$; mean performance levels for this subsample are shown in Table 1). The relationship between SES and verb performance remained of the same size, although the reduced participant numbers meant that the relationships were no longer statistically significant: regular: $R^2 = .013$, $F(1, 62) = .82$, $p = .368$; irregular, $R^2 = .047$, $F(1, 62) = 3.08$, $p = .084$; interaction, $F(1, 62) = 1.79$, $p = .186$, $\eta_p^2 = .028$. The fact that there was a consistent relationship when ceiling effects were removed implies that the difference in the predictive power of SES between regular and irregular verbs is a real one, and provides more evidence for the differential effect of SES across parts of language. The low proportion of variance accounted for by SES in regular past-tense formation is consistent with the findings of Rice et al. (1998; see also Pruitt & Oetting, 2009; Pruitt, Oetting, & Hegarty, 2011).

In sum, then, in a large sample of 6-year-old children, SES effects were observed in English past-tense performance. A regularity effect was present in both mean performance and the predictive power of SES, with SES picking up between 1% and 5% of population variance.

Computational Modeling

The computational modeling of SES effects proceeded as follows. We specified a base or "normal" model of the acquisition of English past tense. We then designed a manipulation to the training environment, corresponding to the family in which simulated children were to be raised. We next designed a manipulation to the efficiency of the learning system, corresponding to the genetic contribution to individual differences. Henceforth, we refer to this as *intrinsic* rather than genetic variability, because it refers to the property of the past-tense learning system. The property must be an outcome of a prior developmental process that constructed the learning system, a process that will have both genetic and environmental contributions (whether cognitive or biological). Finally, we generated a large population of simulated individuals, each of whom underwent a developmental process of acquiring the English past tense. Population performance and the predictive power of environmental variations were then assessed.

We encountered two challenges in pursuing this design, one practical and one theoretical. First, population modeling by its nature necessitates the simulation of large numbers of individuals. Practically, this required simplifications to the base model. (Each simplified model took 2 hr to train and test, and we report on the results of 6,000 networks in the following sections.) The simplification led to limitations in the performance of the base model, but given the advanced state of past-tense modeling, these were well understood. The simplifications involved the use of an artificial language-like training set analogous to English past tense, rather than English verbs themselves (following Plunkett & Marchman, 1991, 1993, rather than Joanisse & Seidenberg, 1999); and training solely on the past-tense paradigm for verbs, rather than simulating a system that learns all inflection types across multiple grammatical classes (see Karaminis & Thomas, 2010). Nevertheless, the artificial language used in the Plunkett and Marchman (1991, 1993) model was successful in demonstrating how the onset and developmental course of overgeneralization errors can emerge in a model trained to map verb stems to past-tense forms. That model also showed the importance for performance of type and token frequency of stems in the input set, as well as the degree to which the phonological shape of the stem is a predictor of mapping pattern.

The second, theoretical challenge is that we did not know a priori the relative range of variability of environmental and intrinsic factors in our population of real children. Do actual environments vary just a little bit, with most environments providing decent information for the children, while intrinsic factors vary more widely, from very poor to very good learning systems? Or are all the children's learning systems reasonably efficient, while the linguistic environment varies greatly in its quality between children? Because empirical evidence was not available to constrain this aspect of the model, we simulated two levels of envi-

[1] Three participants had unusually low regular verb performance, falling below 20% correct. They had SES values of −0.22, −1.39, and 0.44. With these participants excluded, the remaining 267 children showed a reliable relationship between SES and regular verb performance at the .05 level, while the relationship between SES and irregular verb performance, as well as the interaction of SES and verb type, remained unchanged: regular, $R^2 = .016$, $F(1, 265) = 4.35$, $p = .038$; irregular, $R^2 = .047$, $F(1, 265) = 13.13$, $p < .001$; interaction, $F(1, 265) = 9.20$, $p = .003$, $\eta_p^2 = .034$.

Table 1
A Comparison of English Past-Tense Performance of the Bishop (2005) Sample of 270 Six-Year-Old Children on the Rice–Wexler Test and Simulation Data

	Data		Simulation condition (N = 1,000 per population)					
Measure	N = 270	N = 64	IN-EN	IN-EW	IW-EN	IW-EW	IW-EN Variant 1	IW-EN Variant 2
Regular verbs	96 (12)	83 (20)	79 (19)	66 (30)	66 (31)	62 (31)	79 (26)	80 (25)
Irregular verbs	42 (25)	39 (32)	42 (25)	42 (28)	42 (30)	40 (29)	42 (24)	42 (29)
OG errors	46 (46)	38 (26)	16 (12)	17 (13)	9 (10)	12 (12)	21 (15)	23 (20)
Finiteness	91 (12)	80 (20)	68 (20)	62 (29)	59 (30)	57 (30)	71 (26)	72 (26)

Note. Empirical data are for the full sample and also a subsample of children excluding those who had regular verb but not irregular verb performance at ceiling. Simulation data are distinguished by relative range of variation (N = narrow, W = wide) of Intrinsic factors (I) or Environmental information (E). In addition, data for two variant simulation conditions are shown, where the environmental information for irregular verbs was poorer than that for regular verbs. Values show mean accuracy and, in parentheses, standard deviation. OG = overgeneralization.

ronmental variation and two of intrinsic variation. One of the goals of the simulation was to determine which combination gave the best fit to the past-tense empirical data. In future work, ranges could be calibrated to give a precise data fit.

The way in which we addressed the two challenges meant that it was important for us to clearly specify the criteria for success and failure of the simulations in accounting for SES effects in past-tense acquisition.

Criteria for Evaluation the Success or Failure of the Modeling

Because population modeling necessitated the use of a simplified base model of past-tense acquisition, we evaluated the success of the model on the qualitative fit to the empirical data rather than the quantitative fit. Ways to improve the quantitative fit are discussed later. We evaluated the success of the simulations on three

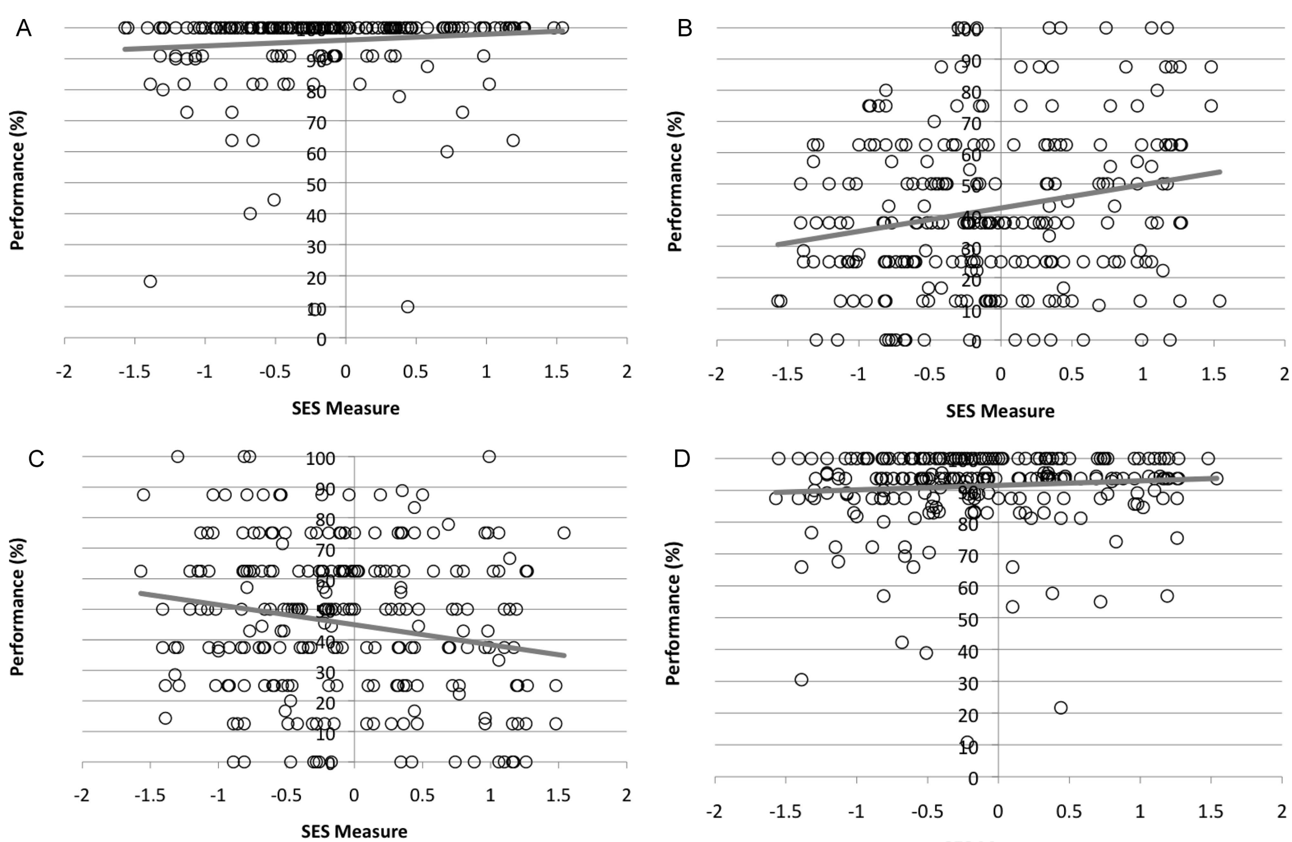

Figure 1. Scatter diagrams relating socioeconomic status (SES; Petrill et al., 2004) to past-tense performance on the Rice–Wexler test (Rice & Wexler, 2001) for 270 six-year-old children (Bishop, 2005). Data show the accuracy of production of regular past tenses (A) and irregular past tenses (B), the proportion of overgeneralization errors for irregular verbs (C), and the proportion of finite responses (D; N = 270 per plot).

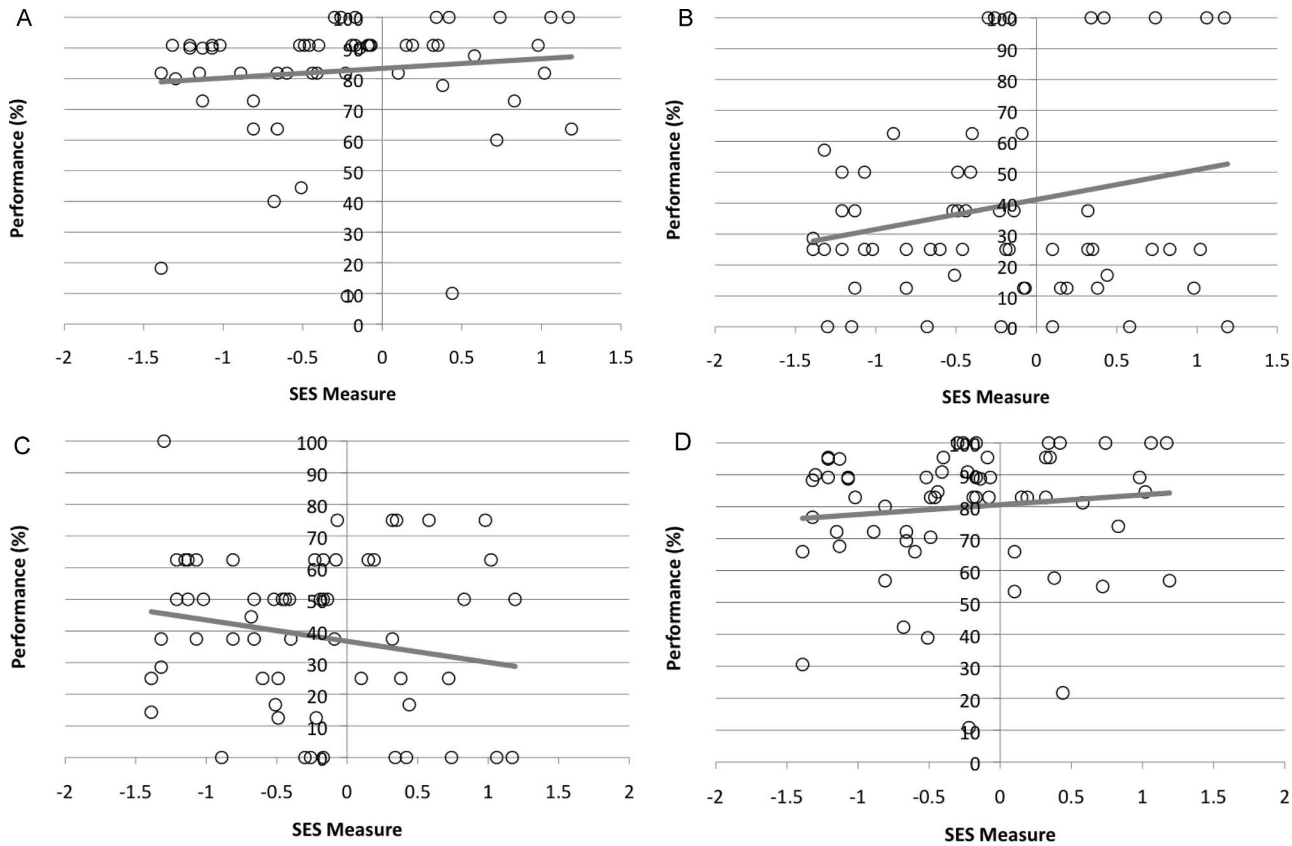

Figure 2. Data from Figure 1 showing the accuracy of production of regular past tenses (A) and irregular past tenses (B), the proportion of overgeneralization errors for irregular verbs (C), and the proportion of finite responses (D), with children removed who were at ceiling on regular but not irregular past-tense production ($N = 64$ per plot). SES = socioeconomic.

criteria: (a) the qualitative fit to size of SES effects in predicting individual variability across each population, and the differential pattern across regular verbs, irregular verbs, overgeneralization errors, and proportion of finite responses; (b) the generation of novel testable predictions (we generated four such predictions, one of which we were able to test against the Bishop, 2005, data set); and (c) the generation of insights on candidate inferences from behavior to mechanism, which is the particular contribution of computational modeling. The latter involved establishing what types of modeling condition led to what types of behavioral data and assessing whether these are the conditions of the cognitive system that researchers typically infer from these types of behavioral data.

Method

Architecture

Recent computational models of English past-tense acquisition have used artificial neural networks (connectionist networks) to learn the association between the phonological form of the verb stem and the past-tense form. Along with the verb stem, other sources of information are provided at input, including lexical–semantic information, and information about the desired output inflection (Karaminis & Thomas, 2010; Woollams, Joanisse, & Patterson, 2009). It should be noted some researchers maintain that symbolic approaches are more appropriate for explaining past-tense acquisition, at least for regular verbs, where regularity is viewed as reflecting the operation of a rule-based mechanism (Pinker, 1999). However, these more linguistically oriented theories have not typically been realized in computational implementations of the developmental process. In the current simulations, a three-layer, backpropagation network was used to learn to output a phonological representation of the past-tense form of a verb from an input vector combining a phonological representation of the verb stem and lexical–semantic information. The architecture is shown in Figure 3.

Training Set

For our training set, we used the "phone" vocabulary from the Plunkett and Marchman (1991, p. 70) past-tense model. This comprised an artificial language set constructed to reflect many of the important structural features of English past-tense formation. There were 500 monosyllabic verbs, constructed with consonant–vowel templates and the phoneme set of English, and split into 410 regular verbs and 90 irregular verbs of three types: no change, vowel change, and arbitrary. A set of novel verbs was also con-

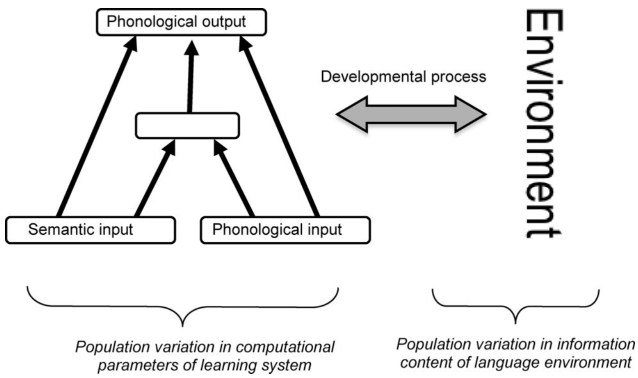

Figure 3. Architecture of the past-tense model.

structed to test generalization of the regular past-tense rule. Further details on the construction of the training set can be found in supplemental materials.

Implementing Environmental Variation

Our principal goal was to test the viability of the proposal that SES effects on language acquisition are the result of variations in the input. More formally, this means that variations in SES result in a transform applied to the information the child exploits to acquire a given feature of language. For implementation, the key question is how the transform alters the quantity versus the quality of the input. The empirical literature here does not yet give a definitive answer.

Initial studies investigating vocabulary growth focused on the quantity of language to which children are exposed (Hoff-Ginsberg, 1991, 1992; Huttenlocher, Haight, Bryk, Seltzer, & Lyons, 1991). Across a range of language features, Hart and Risley (1995) found that the most striking differences in input were in amount rather than richness (e.g., children in professional families were exposed to 36 past tenses per hour on average, whereas those in working-class families were exposed to 25 past tenses per hour, and those in welfare families only 8 per hour; p. 243, Figure 11). Nevertheless, Hart and Risley (1992) reported that in general parents who used more words tended to use a greater variety of words and in longer sentences. Studies of vocabulary growth have indicated that children exposed to more varied vocabulary improved more quickly (Hoff, 2003), and that this influence could be independent of the quantity of child-directed speech (Huttenlocher et al., 2010; Pan, Rowe, Singer, & Snow, 2005). Huttenlocher et al. (2010) found that this effect also held for syntactic diversity, while quantity influenced the order of emergence of structures within a child.

On the basis of this literature, we chose to implement the transform on the past-tense input as a modulation of the type frequency of verbs. A lower SES family would be modeled as using fewer past tenses overall, fewer types of regular verbs, and fewer types of irregular verbs. This implementation captures both the reduced diversity of vocabulary in lower SES families and the reduced quantity of past tenses experienced by the child. In machine learning terms, we operationalized environmental variation as a (potentially time-varying) function with respect to the training set. We assumed that there was a "perfect training set," in this case comprising all of the verbs available in the language, along with their accepted past-tense forms. We defined the function for variations in the training set as follows:

$$\text{Training set } P_n T_t = f\{\text{perfect training set}, X, Y, Z\}. \tag{1}$$

The training set for person n at time t is a function f of the perfect training set and three parameters: X = proportion of valid training trials, Y = proportion of invalid training trials, and Z = proportion of noise trials. Invalid trials have the same input as a training pattern but a different output. Noise trials have different inputs and outputs or include partial information consistent with training patterns. In principle, the function f could be influenced by person n's behavior or experiences at $t - 1$, creating a more complex dynamical equation. A dynamical equation would accommodate the possibility of, for instance, a reduced reward leading to reduced attention and therefore a subsequently smaller proportion of valid training trials.

We made the following assumptions in our implementation. First, once instantiated, we gave each network a *preconditioning* phase to produce divergent initial connection weights. This comprised a version of the training set with X set to 0, Y set to 0, and Z set to 1. The training set was made up of 30 random binary vectors at input and output, uniquely created for each individual, and trained for 50 epochs. This phase was intended to simulate the effect of early subjective experience prior to using the relevant learning system for (in this case) modulating phonological output forms via tense information. Next, we created a training set for the past-tense information available in each family environment. To do so, we generated a *family quotient* for each simulated child. This was our implementation of SES. The family quotient was a number between 0% and 100%. This value was used as a probability determining whether each verb in the perfect training set would be included in the family's vocabulary. In terms of Equation 1, X = family quotient, $Y = 0$, $Z = 0$. The family training set was then fixed throughout development. However, performance was always assessed against the full perfect training set (analogous to a standardized test of past-tense formation applied to all children). The family quotient manipulation corresponds to a reduction in type frequency for both regular and irregular verbs, while the token frequency of each verb (3 times greater presentation for high than low frequency) was retained.

Our final decision was how to sample the family quotient values. The composite SES measure used for the Bishop (2005) sample of twins had a normal distribution with large standard deviation and a negative skew. Another twin study examining SES effects on cognition with a large sample of 287 school-age children (Hart et al., 2007) reported maternal education data that were normally distributed with a large standard deviation and a positive skew. In the end, we selected a uniform distribution, which slightly exaggerated the incidence of high and low SES. We selected two ranges of environmental variation: a narrow range with reasonably high quality, sampling family quotient values between 60% and 100%, and a wide range that accommodated potentially very poor quality environments, sampling quotient values between 0% and 100%. These manipulations were applied equally to regular and irregular verbs.

Due to simulation results with lower rates of overgeneralization errors than those found in the empirical data, we considered two further manipulations in which irregular verb information was poorer than that for regular verbs. These were exploratory conditions that were not constrained by existing empirical data and evaluated the hypothesis that the rate of overgeneralization might in part be driven by impoverished irregular verb information received from the environment. The rationale was that since irregular verbs are harder to learn and more prone to errors in production, children might experience either lower quality or more variability in the input they receive for irregular verbs than regular verbs—especially to the extent that some of the language input to older children comes from their peers, who are likely to make overgeneralization errors. In Variant 1, two family quotient values were independently sampled for each simulated child. Regular verbs were sampled between 60% and 100% (mean 80%), and irregular verbs were sampled in the range 40%–80% (mean 60%). This manipulation had identical range of variation but a lower absolute level for irregular verbs. In Variant 2, a lower absolute level for irregulars was achieved by widening the range: Irregular verbs were sampled between 20% and 100% (mean 60%). These manipulations were simplified in that they distinguished categorically between regular and irregular verbs (see Discussion).

Implementing Intrinsic Variation

Connectionist networks contain a range of parameters that increase or decrease their ability to learn a given training set. Parameters such as learning rate, momentum, and number of hidden units feature in most published simulations. In models of normal or average development, such parameters are usually optimized to achieve best learning (usually in the presence of the perfect training set). Certain parameters have been proposed as candidates to explain individual differences, search as the learning rate (as a proxy for neuroplasticity; Garlick, 2002), or use of differential processing routes connecting input and output (Harm & Seidenberg, 2004). However, a given parameter may have differential effects across the parts of a problem domain. For example, Thomas (2005) demonstrated how the "temperature" or steepness of the sigmoid activation function in the artificial neurons had more effect on regular than irregular verbs in past-tense acquisition. To remain neutral with regard to which parametric variations were responsible for intrinsic variation in the learning system, we simultaneously varied a number of parameters across individuals. As with environmental variation, we considered two ranges of intrinsic variation, either narrow or wide.

Fourteen computational parameters were allowed to vary between individuals, serving to alter the learning capacity of each network. The parameter settings allowed for over 2,000 billion unique individuals. The parameters, split by their role, were as follows: (a) network construction: architecture, number of hidden units, range for initial connection weight randomization, and sparseness of initial connectivity between layers; (b) network activation: unit threshold function, processing noise, and response accuracy threshold; (c) network adaptation: backpropagation error metric, learning rate, and momentum; (d) network maintenance: weight decay, pruning onset, pruning probability, and pruning threshold. The parameter ranges for narrow and wide intrinsic variation can be found in the supplemental materials (Table S1).[2]

Design

For each population, 1,000 sets of the 14 computational parameter values were generated. These were instantiated as 1,000 connectionist networks, which were then trained as follows. The individual was trained initially on a unique preconditioning training set to produce unique and divergent starting weights. A family quotient value was then generated from the appropriate range and used to create the family training set. Following preconditioning, each network was trained for 1,000 epochs on its family training set. At each epoch, performance was measured on the perfect training set. Performance was assessed on regular verbs, irregular verbs, overgeneralization errors, and generalization of the past-tense rule to novel forms. Performance was measured in nearest-neighbor accuracy levels (percent correct). Four populations were run in a 2 $\times$ 2 design, of narrow or wide environmental variation and narrow or wide intrinsic variation, to assess which combination of variability would best explain the Bishop (2005) data.

Since the Bishop (2005) data comprised twin pairs, this constraint was built into the simulations as well. Network parameter sets were encoded in an artificial genome. Monozygotic (MZ) twins were created by pairs that had identical genomes, whereas dizygotic (DZ) twins had genomes that shared 50% of their genes on average. Twin pairs were assigned the same family training set (see Footnote 2). Each population comprised 250 MZ and 250 DZ twin pairs. We address the similarity between twin behavior and its implication for heritability of past-tense formation in a separate work (Thomas, Forrester, & Ronald, 2012) and do not consider twin status further here.

Results

Mean Levels

The Rice–Wexler test (Rice & Wexler, 2001) contains primarily vowel-change irregular past tenses. The simulated populations were benchmarked to the point in training where the mean accuracy of irregular vowel-change verbs was equivalent to the Bishop (2005) sample. Results for the four populations in the 2 $\times$ 2 design are included in Table 1. It is immediately obvious that when matched on irregular verb performance, both regular verb performance and the rate of overgeneralization errors were lower in all populations than in the children. There are four potential reasons why this disparity occurred. First, it could be due to the simplifications in our base model. Recent models of past-tense formation include aspects of their design and training that serve to support regular past-tense formation, aspects not present in the base model. These include training on the verb stem at output, which is the main component of a regular past-tense form, and the provision of a "past-tense unit" at input, which forms a strong association to the past-tense inflection at output (Karaminis & Thomas, 2010; Woollams et al., 2009). Second, model performance was tested on the full training set, including high- and low-frequency items, whereas the empirical data were for a restricted set of regular and irregular verbs; as discussed in the supplementary materials, in the Bishop sample's performance on the Rice–Wexler test, the influence of regularity was higher than that found in other past-tense elicitation

[2] Technical details of the parameters, the methods for establishing their range, and generation of the populations can be found in a technical report available online (http://www.psyc.bbk.ac.uk/research/DNL/techreport/Thomas_paramtables_TR2011-2.pdf).

tasks. Third, because the children in the Bishop study were drawn from a group oversampled for risk of language disorder, it is possible that some children had small residual deficits, or the language of the parents was atypical in a way not modeled here (early risk of language delay explained a small amount of variance in the children's performance at age 6). Finally, it may be that the greater influence of regularity in the Bishop data represents an environmental effect, namely, that for the children, irregular verb information is poorer than regular information. Perhaps some children are raised in a linguistic environment where parents and peers make more errors on irregular than regular verbs. For example, in some dialects covarying with SES, some irregular forms may be regularized. If irregular verb performance was lower at a population level, for a given level of irregular performance, regular performance would be higher and there would be more overgeneralization errors.

We tested this last idea by running two additional conditions where irregular information was poorer on average than regular information. In Variant 1 we lowered the absolute level of the family quotient value for irregular verbs but kept the range the same. In Variant 2 we lower the absolute level but also widened the range of family quotient values for irregulars. These were run for a population with wide intrinsic variation. Table 1 (rightmost columns) shows that such a manipulation indeed raised the relative level of regular verb performance compared to irregulars and increased the rate of overgeneralization errors. However, the population means still demonstrated a shortfall in the influence of regularity compared to the full sample. We now shift to our main focus, factors predicting individual differences in the populations.

Predictive Power of SES

The family quotient value was used as a proxy for SES and used to predict individual differences in past-tense performance for the 2×2 design. Table 2 compares simulation results for the four populations, and Figure 4 demonstrates the scatterplots for comparison with Figure 1.

We refer to the populations by whether the intrinsic variation (I) was narrow (N) or wide (W), and whether the environmental variation (E) was narrow or wide. For the simulations, the conditions with narrow environmental variation demonstrated a reliable regularity effect, where SES was a stronger predictor of irregular verb performance than regular verb performance; when the environment varied widely in quality, this drove performance on regular and irregular verbs to a similar extent: interaction of regularity and environmental variation, $F(1, 3992) = 37.53$, $p < .001$. The regularity effect was not modulated according to whether intrinsic variation was narrow or wide, $F(1, 3992) = 0.00$, $p = .974$. Only when intrinsic variation was wide did the negligible predictive power of SES on regular verbs emerge (IW-EN). This condition therefore represents the best qualitative fit to the empirical data. The condition did, however, overestimate the predictive power of SES on overgeneralization errors. Of the two variant conditions, there was again a strong regularity effect, but Variant 2 (where the range of variation of irregular information was widened compared to regular verbs) displayed much higher SES predictive power for irregulars and overgeneralization errors. Notably, despite this difference in the influence of the environment, the two variants had identical mean levels of performance (see Table 1). Taking into account both predictive power and mean levels of performance across the measures, the best fit was the wide-intrinsic/narrow-environmental variation Variant 1 condition, which had the same range of variation for irregular verbs but at a lower level of quality.

Some caution is necessary in directly mapping between data and model, because the model contains no measurement error either in the family quotient or in past-tense performance. In reality, SES is measured by variables such as parental income and education, which can only give an estimate of actual causal factors. In addition, we know that the Rice–Wexler test has some measurement error, indicated by its test–retest reliability of .8 (Rice & Wexler, 2001). With measurement error added to the simulations, the predictive power of our SES proxy would be reduced.

Novel Predictions

SES and delay versus giftedness. We used the model to predict the extent to which variation in the information available in the environment could predict whether individuals would fall in the bottom or top 10% of the population, equivalent to developmental delay or giftedness. This analysis was carried out separately for the four dependent measures, at the point in development when the models were matched to the performance level of the Bishop

Table 2
A Comparison of the Predictive Power of Socioeconomic Status on English Past-Tense Performance of the Bishop (2005) Sample of 270 Six-Year-Old Children on the Rice–Wexler Test and Simulation Data

	Data		Simulation condition (% variance explained)					
Measure	% variance explained	p	IN-EN	IN-EW	IW-EN	IW-EW	IW-EN Variant 1	IW-EN Variant 2
Regular verbs	1.3	.060	6.2	70.0	0.8	44.2	2.7	0.0
95% CI	[0.0, 4.4]		[4.0, 8.8]	[67.3, 72.5]	[0.1, 2.0]	[40.3, 48.0]	[1.3, 4.6]	[0.0, 0.0]
Irregular verbs	4.7	.000	7.6	69.9	2.6	43.7	6.7	25.2
95% CI	[1.4, 9.6]		[5.1, 10.4]	[67.2, 72.4]	[1.2, 4.5]	[39.8, 47.5]	[4.4, 9.4]	[21.3, 29.1]
OG errors	3.8	.001	12.1	3.3	11.3	7.0	3.2	32.1
95% CI	[0.9, 8.3]		[9.1, 15.4]	[1.7, 5.4]	[8.4, 14.5]	[4.6, 9.7]	[1.6, 5.2]	[28.1, 36.1]
Finiteness	0.7	.170	3.6	65.8	0.5	37.1	2.3	0.4
95% CI	[0.0, 3.3]		[1.9, 5.7]	[62.8, 68.6]	[0.0, 1.5]	[33.1, 41.0]	[1.0, 4.1]	[0.0, 1.3]

Note. Simulation data are shown according to relative range of variation (N = narrow, W = wide) of Intrinsic factors (I) or Environmental information (E). In the variant conditions, where the environmental information for irregular verbs was poorer than that for regular verbs, the mean value of the family quotient was used to predict performance. Confidence intervals (CIs) are around the R^2 value. OG = overgeneralization.

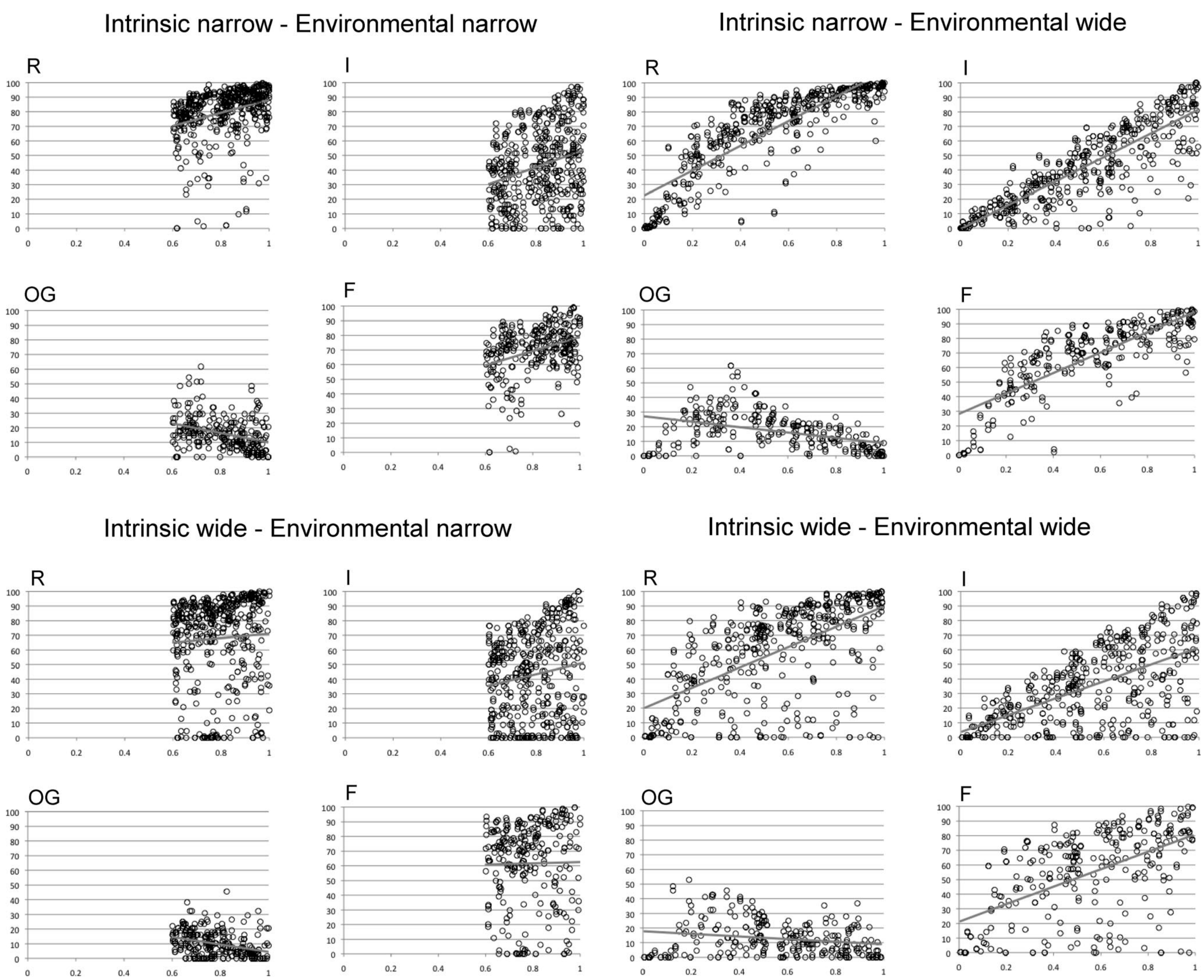

Figure 4. Scatter diagrams relating family quotient values (the socioeconomic status proxy; *x*-axis) to past-tense performance for the model (*y*-axis). Simulated data are for the 2 × 2 design with a narrow or wide range of intrinsic variation and a narrow or wide range of environmental variation, for regular verbs (R), irregular verbs (I), overgeneralization errors (OG), and finite responses (F; N = 1,000 per plot).

(2005) sample on irregular verb performance. For overgeneralization errors, better performance was scored as fewer errors. The results are shown in Tables 3 and 4.

From the previous section, the conditions with narrow environmental variation were closer to fitting the predictive power of SES for all the 6-year-old children. Here these conditions suggested that SES should be able to predict whether children were gifted but barely (if at all) able to predict whether children were delayed. To our knowledge, this novel prediction has not been made by any other theory of individual differences. Broadly, this pattern arises because there are many ways to fail but few ways to succeed: In the bottom tail, the predictive power of any one factor is therefore diluted. We consider this point in more detail in the Discussion. The prediction was testable with the Bishop (2005) data set, and the results are shown in Table 4. The data confirm that SES reliably predicted whether children would be in the top 10% of the population for regular verb performance, irregular verb performance, and the rate of overgeneralization. SES did not predict delay for any of the dependent measures. This result provides powerful support for the model.

SES effects across development. The empirical data set provides a snapshot of the predictive power of SES at a single point in time. The simulations allow us to predict where the snapshot would fall within a developmental trajectory. That is, for our 2 × 2 design, we can assess whether SES effects should rise or fall with age. Surprisingly, the model predicted that SES effects should rise across development (see Figure S1 in the supplemental materials for example data illustrating this effect). The rise was most marked for the conditions with wide environmental variation. For these conditions, the environment becomes the limiting factor on the best performance that an individual can achieve. The pathway to this endpoint, by contrast, is influenced by the computational

Table 3
Role of the Environment in Predicting Performance in the Tails for the Simulations

Measure	Narrow		Wide	
	Delayed	Gifted	Delayed	Gifted
Narrow				
Regular	1.2	11.1	23.2	21.5
95% CI	[0.3, 2.6]	[8.2, 14.3]	[19.4, 27.1]	[17.8, 25.3]
Irregular	0.6	8.7	15.3	21.9
95% CI	[0.1, 1.7]	[6.1, 11.7]	[12.0, 18.9]	[18.1, 25.8]
OG errors	1.6	4.8	1.9	3.9
95% CI	[0.6, 3.1]	[2.9, 7.2]	[0.7, 3.6]	[2.2, 6.1]
Finiteness	0.7	5.6	22.3	19.0
95% CI	[0.1, 1.8]	[3.5, 8.1]	[18.5, 26.2]	[15.4, 22.7]
Wide				
Regular	0.0	11.5	7.1	19.2
95% CI	[0.0, 0.4]	[8.5, 14.8]	[4.7, 9.9]	[15.6, 30.0]
Irregular	0.0	11.8	3.3	19.0
95% CI	[0.0, 0.3]	[8.8, 15.1]	[1.7, 5.4]	[15.4–22.7]
OG errors	1.3	2.3	3.1	1.2
95% CI	[0.3, 2.7]	[1.0, 4.1]	[1.6, 5.1]	[0.3, 2.6]
Finiteness	0.0	6.8	7.0	15.6
95% CI	[0.0, 0.5]	[4.5, 9.5]	[4.6, 9.7]	[12.2, 19.2]

Note. Environmental index was family quotient value. Values show percentage of variance explained. Confidence intervals (CIs) are around the R^2 value. Delayed = bottom 10% of population; gifted = top 10% of population; OG = overgeneralization.

properties of the learning system. That is, when environmental variability is wide, intrinsic factors may alter rate of development, but environmental factors will be a strong predictor of ceiling performance. This prediction remains to be tested against longitudinal data for past-tense acquisition.

Generalization to diagnose the locus of environmental influence on development. Some tests of past-tense acquisition elicit novel past tenses from children, for words they have not heard before. The Rice–Wexler test (Rice & Wexler, 2001) did not include this condition. The inflection of novel verbs necessarily tests the generalization ability of the system, rather than its storage of the past-tense forms that it had previously encountered. Generalization sometimes serves as a better index of the computational properties of a learning system than its ability to memorize knowledge. For the model, we compared the predictive power of the family quotient variable on individual performance for information in the training set (regular and irregular verbs) to generalization performance on a set of novel verbs. To get a robust view of the relationship of the verb types, the percentage variance explained was calculated across a tranche of development, from Epoch 50 to Epoch 250 in each population. The mean of the 200 R^2 values for each verb type are shown in Table 5.

When there was wide variability of information in the environment, family quotient predicted substantial variability in performance both on verbs in the training set and on generalization. When the computational properties of the learning system were the more prominent factor, environmental variability predicted less variance in performance on the training set, but negligible amounts of variability on generalization (falling to zero when intrinsic variability was wide and environmental narrow). These interactions were all highly reliable when analyzed with a mixed analysis of variance.

The relevance of this finding is that, as noted in the introduction, SES may in principle affect either the information in the environment or the computational properties of the learning system (via perinatal or postnatal biological effects on brain function). In the preceding simulations, we have focused on the former possibility. Generalization is a closer index of the computation properties of a learning system than performance on the training set. Therefore, it may serve to isolate the locus of environmental effects: The simulations suggest that a comparison of the ability of SES to predict variability in performance on children's knowledge (training set) versus extension of that knowledge to novel forms (generalization) may be one way to untangle whether a given SES effect operates via the information content of the environment or via influencing learning systems themselves.

Interactions between SES and ability: Gene–environment interactions and resilience. In this section, we assess whether the model predicts interactions between SES and child internal factors, such that the influence of SES might differ at different ability levels. In particular, high SES is sometimes thought of as a protective factor conferring resilience on child development. To investigate this idea, we needed to establish the intrinsic "ability level" of each network. This was calculated based on the contri-

Table 4
Role of the Environment in Predicting Performance in the Tails for the Bishop (2005) Sample of 270 Six-Year-Old Children on the Rice–Wexler Test

Measure	Delayed			Gifted		
	% explained	95% CI	*p*	% explained	95% CI	*p*
Regular	0.9	[0.0, 3.7]	.117	3.5	[0.8, 7.9]	.002
Irregular	0.2	[0.0, 2.1]	.493	3.6	[0.8, 8.1]	.002
OG errors	0.8	[0.0, 3.5]	.138	2.2	[0.2, 6.0]	.016
Finiteness	0.6	[0.0, 3.1]	.204	0.1	[0.0, 1.7]	.595

Note. Environmental index was socioeconomic status. Values show percentage of variance explained. Confidence intervals (CIs) are around the R^2 value. Delayed = bottom 10% of population; gifted = top 10% of population; OG = overgeneralization.

Table 5
Predictive Power of Variation in the Information Available in the Environment for Learning the Training Set Versus Generalization for the Simulations

Variable	Variability of environmental information			
	Wide		Narrow	
	Variability of intrinsic computational properties			
	Wide	Narrow	Wide	Narrow
Training set				
Regular verbs	34.3 (4.1)	68.8 (3.5)	0.8 (0.1)	11.9 (3.0)
Irregular verbs	29.3 (5.9)	67.1 (10.5)	2.3 (0.6)	15.8 (4.8)
Generalization				
Novel verbs	24.7 (1.9)	52.2 (1.5)	0.0 (0.0)	2.7 (0.0)

Note. Values show percentage of variance explained by the environmental index, family quotient value, averaged over Epochs 50–250 for each modeling condition. Values in parentheses depict the standard deviation of these 200 R^2 values.

bution of each network's parameter set to predicting its performance. We selected a given point in training and then used the computational parameter sets and the family quotient value in a multiple regression model to predict population performance. The subsequent regression coefficients revealed the influence of each computational parameter in driving an individual's performance. A weighted sum of each individual's computational parameter values and their regression coefficients then yielded a single number, which represented the contribution of that network's learning ability to its performance. This exercise was carried out for the wide-intrinsic conditions, with either narrow or wide environment, at a point in training when irregular verb performance was matched to that of the Bishop (2005) sample. Irregular performance was used as the dependent measure, since it provided a sensitive measure. Using the derived ability index, we split the population into four levels. We similarly split the family quotient value into four levels. Figure 5A plots the predicted effect of environmental variation for the intrinsic-wide/environmental-

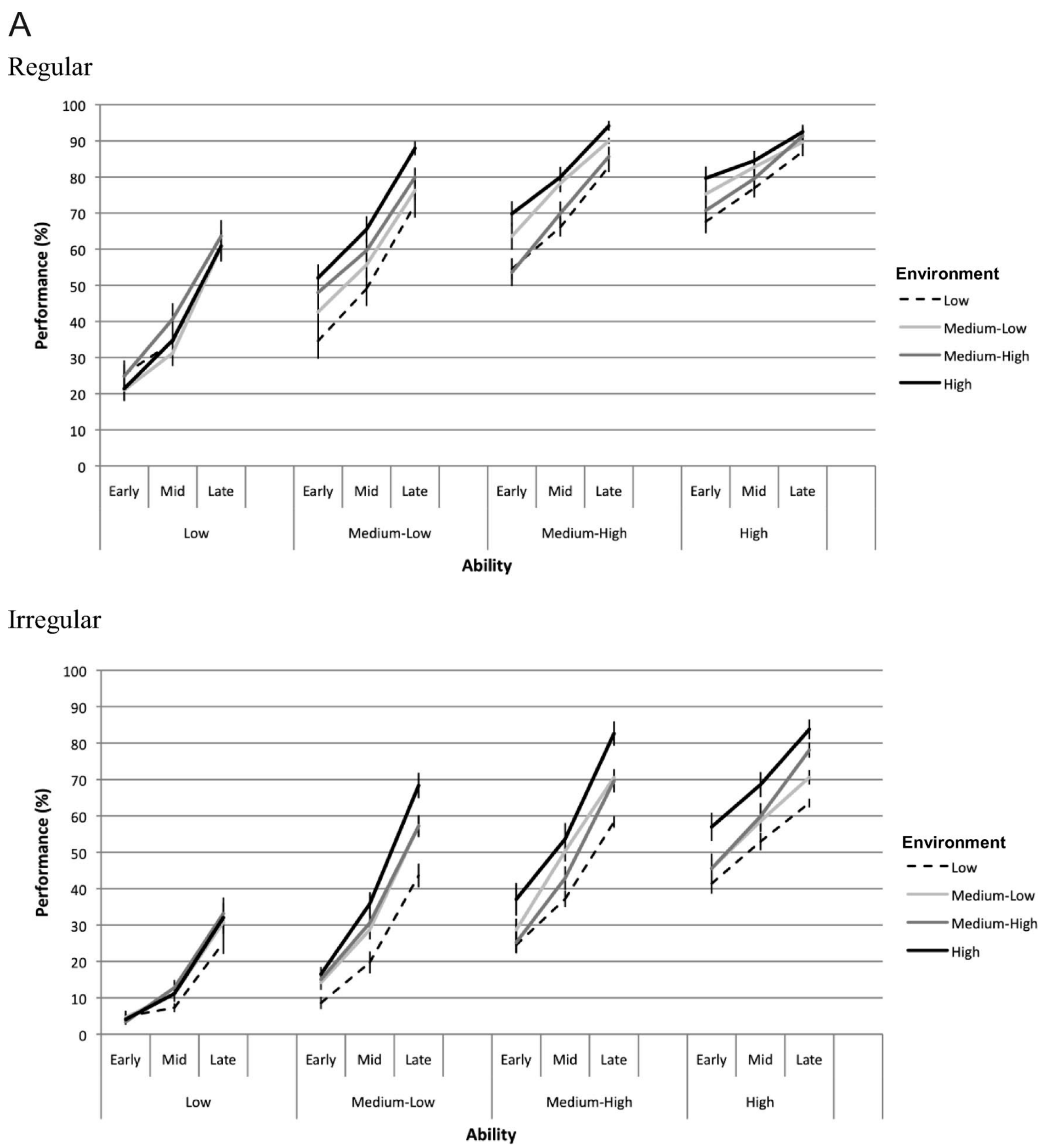

Figure 5. Predicted gene–environment interactions across development, where genetic effects are assumed to operate via variations in intrinsic neurocomputational parameters that affect learning ability, and environmental effects are assumed to operate via variations in the information available in the input. Results for wide intrinsic variability and narrow environmental variability (A); results for wide intrinsic variability and wide environmental variability (B). Early = 50 epochs of training; Mid = 100 epochs of training; Late = 750 epochs of training.

narrow condition on networks of different ability at three points across development.

The model predicted a minor interaction between SES variation and ability level. For this population, ability was a much stronger predictor of performance than SES (40% vs. 4% of the variance), although both effects were statistically reliable. For low-ability networks, the variation produced by differences in the input was reduced, a pattern that was consistent across development. Figure 5B shows comparable results for the wide-intrinsic/wide-extrinsic condition, where the influences of ability and input were more equal (30% vs. 42%). Here there was a much starker demonstration that input variations had a greater effect in higher ability networks and, moreover, particularly for irregular verbs, that this effect became exaggerated across development. (These results were all reliable when analyzed with a mixed-design analysis of variance.) In sum, the model predicted that under conditions of wide environmental variation, in high-ability children the influence of SES should become ever more exaggerated across development.

We were struck by the fact that the model did not predict a resilience role for either variations in the input or in intrinsic factors. On the contrary, low ability squashed the variation due to environmental factors, whereas high ability allowed its expression (and vice versa: low environment squashed the variation due to ability, whereas high environment allowed its expression).

Under what conditions could the model exhibit resilience effects? We have focused on evaluating the idea that SES might

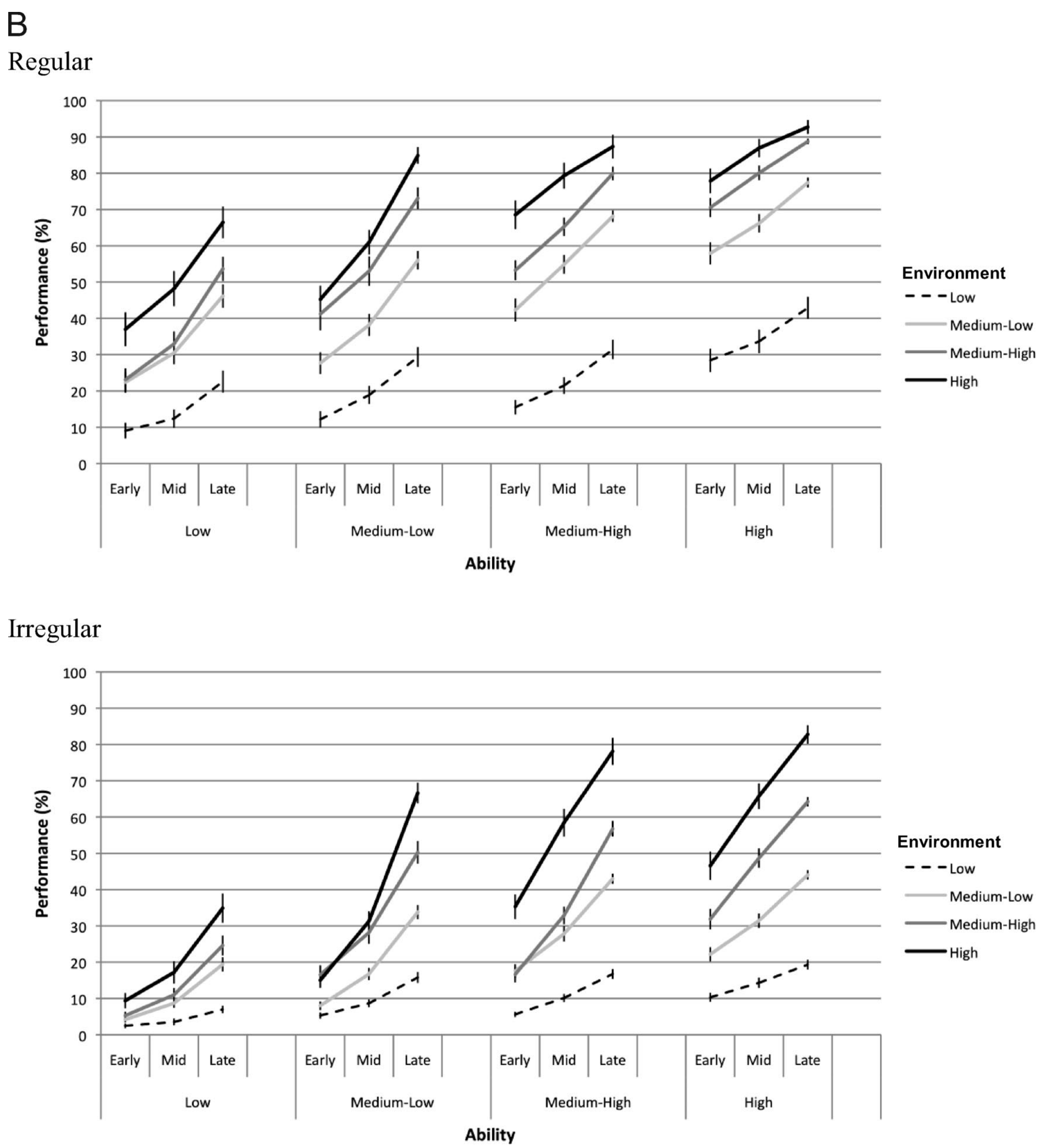

Figure 5. (*continued*)

operate through variations on the input. However, we also allowed the idea that SES might influence properties of the learning system, through perinatal or postnatal effects. It was indeed possible to identify pairs of computational properties that bore a resilience relationship to each other, but not all did so. Figure 6 depicts two situations, comparing the performance of subsets of individuals from the wide-intrinsic/narrow-environmental condition. In the first situation, we assumed that genotypic variation operated on the learning rate inside the network, whereas environmental effects operated on the number of internal units (assuming, for example, a perinatal influence on neural proliferation and migration, or a postnatal influence of chronic stress on the survival of neurons). Figure 6A shows a similar pattern to that in Figure 5: Low ability squashes environmental variation, whereas high ability allows its expression. In the second situation, we assumed that the genotypic variation operated on the architecture of the network, determining whether it employed a single pathway or two parallel pathways from input to output (one with internal units, one with direct connections). Environment was once more was assumed to operate on internal units. In Figure 6B a resilience pattern is observed. A two-pathway network was resilient to variations in internal units, whereas a single-pathway network was not. This was because when the number of internal units was reduced, the other (redundant) pathway could take over its function.

The important conclusion is that the model indeed predicted that the effect of variations in SES may depend on child internal factors. Under conditions of *redundancy*, this will manifest as a resilience effect. Otherwise, this interaction will manifest as a pattern of greater SES effects emerging in higher ability children, with these gaps widening across development. If SES operates on the information available in the language input, one would expect interactions of the latter sort.

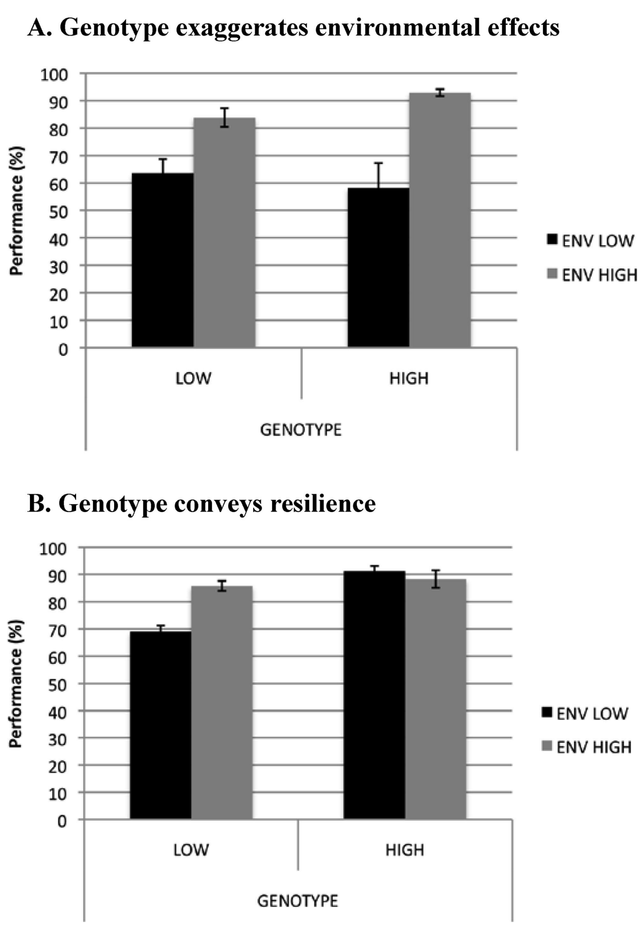

Figure 6. Two examples of predicted gene–environment interactions where genetic and environmental effects are assumed to operate via different neurocomputational parameters affecting learning ability. Environmental effects assumed to operate on number of internal processing units and genetic effects assumed to operate on learning rate (A); environmental effects assumed to operate on number of internal units and genetic effects assumed to operate on architecture (B). (Data are from wide-intrinsic/narrow-environmental condition, for regular verbs late in development.) ENV = environment.

Discussion

To our knowledge, these simulations represent the first attempt to capture the effects of SES in an implemented computational model of language development. There were two ways to implement SES effects within our modeling framework: as an influence on the language input or as an influence on the properties of the learning system. Our main focus was on evaluating the first of these pathways, based on a literature documenting SES effects on child-directed speech and evidence for the causal role of input differences on language development (e.g., Hart & Risley, 1995; Hoff, 2003; Hoff-Ginsberg, 1991, 1992; Huttenlocher et al., 1991, 2002, 2010; Pan et al., 2005). We evaluated the simulation results against three criteria: (a) qualitative fit to the empirical data, (b) novel testable predictions, and (c) insight into inferences from behavior to mechanism. How did the model do?

Qualitative Fit to Data

We evaluated the model on a qualitative rather than quantitative fit to the empirical data for two reasons. This was a first step in modeling SES effects on language development. It involved a number of simplifications to enable population-level simulations. Second, one key assumption of the model was unconstrained by the empirical data: the relative range of variation of environmental versus intrinsic sources of individual differences.

The key characteristics of the target empirical data were stronger performance on regular verbs than irregular verbs, small amounts of variance predicted by SES (between 0.7% and 4.7% of variance across the four dependent measures of past-tense performance assessed), and stronger predictive power of SES on irregular than regular verbs. Qualitatively, the modeling condition best able to capture this pattern was one that combined wide intrinsic variation in the power of the computational learning systems with narrower variation in (and reasonably high quality of) the information content of the environment to which those learning systems were exposed. The regularity effect in population means and in the predictive power of SES emerged despite no differential treatment of regular and irregular verbs in either the architecture or the learning environment. Regular verbs were less sensitive to variation in the environment solely because of their systematic structure: Learning one regular past tense helps in producing another, more than learning one irregular past tense helps in producing another. To some extent, systematicity in the structure of a problem domain serves to liberate the learning system from variations in the information available in the environment.

There was a quantitative mismatch in the population level of regular verb performance when irregular verb performance was matched to the target data. Does the fact that the model cannot adequately learn regular inflections in a simplified data set undermine its validity to investigate SES effects? To address this we need to consider the model simplifications and their impact on the model's behavior. There were four main simplifications: (a) in the base model of past-tense formation, (b) in the nature of the transform that SES applies to the language input, (c) in treating the difference between regulars and irregulars as dichotomous, and (d) in treating intrinsic versus extrinsic sources of variation as independent. With respect to the base model, recent larger scale models include architectural and training constraints that improve performance on regular verbs and generalization, such as additional training on stem outputs or training on multiple inflection paradigms (e.g., Karaminis & Thomas, 2010; Woollams et al., 2009). The lower regular performance in the current model is a likely consequence of its scale.[3] Nevertheless, state-of-the-art models of inflectional morphology are addressed to capturing the development of the average child. Their parameters, in terms of training set, training regime, and learning system, are optimized to simulate that profile. By contrast, the simulation results we report for performance on past-tense production are arithmetic means of a large population; if there is *an* average individual, in our simulations this network will be suboptimal, both in its training set and in its computational parameters. This distinction reflects the different focus of the two modeling enterprises: simulating development alone versus simulating both development and individual differences at the population level.

In a larger scale model, would the predictions of SES effects still hold? The relative importance of extrinsic (environmental) versus intrinsic variation will hold across implementations. However, the size of the interaction between SES and verb regularity is likely to be sensitive to the details of implementation, since the interaction depends on similarity and, in the case of regular verbs, the greater opportunity for the model to use information from one learning event to inform other learning events. Models with a stronger encoding of regularity may exhibit reduced SES effects for regular compared to irregular verbs. In pilot simulations, we used a model that considered past tense solely as a mapping between phonological forms rather than including lexical–semantic information. Those simulations replicated all the main results of the current model, indicating some robustness to variations in the model assumptions.

In terms of the other simplifications, we considered a transform on the type frequency of the input. Of course, the theoretical claim here is that SES produces some kind of transform on the input. A preferable implementation would be one in which the transform is modeled as a modulation of the probability function that any verb form will appear in the input of a given child, a function that is constrained by corpus statistics from child-directed speech in families of different SES levels (e.g., Hall, Nagy, & Linn, 1984). This would enable much finer grained predictions to be made about SES influences on individual verb types. Our dichotomy into regular and irregular verbs did not respect the continuum of regularity that characterizes actual verbs, but was appropriate for the target data set we had available. The aforementioned probability transform would likely interact with this continuum to predict SES influences on individual verbs. In terms of intrinsic and extrinsic sources of variation, we predominantly considered SES effects as operating on properties of the input, whereas more realistically SES might simultaneously influence the input and properties of the learning system. This simplification was justified by our aim to evaluate the viability of the input hypothesis. It is worth noting that in artificial neural network models, performance on irregular verbs is usually more sensitivity to suboptimal processing conditions. Environmental influences on computational learning properties might also produce a differential effect across verb types.

The mismatch between all our initial modeling conditions and the level of overgeneralization errors observed in the Bishop (2005) sample motivated us to consider two exploratory variants of the model. We considered the possibility that knowledge of irregular verbs might be poorer, on the basis that since irregular verbs are harder to inflect, children may hear more errors in irregulars from their caregivers and peers. Hart and Risley (1995) did not distinguish past tenses based on regularity, so data cannot yet directly constrain the possibility of Regularity $\times$ SES interactions on child-directed past-tense information. When we sought to implement the idea of a Regularity $\times$ SES interaction, it became apparent that there is more than one way to achieve this result. Irregular verb information may have a lower absolute level of quality but the same range of variability; or it may have a lower absolute level as well as a wider range of variability. Our simulations demonstrated that either was sufficient to increase the level of overgeneralization errors. Moreover, these variants did not maximize the potential for such errors, since irregular verbs were only omitted from the training set, rather than added in their regularized form. It is of interest that the two variants exhibited equivalent population mean levels of accuracy (see Table 1) but differed in the extent to which measures of the variation in environmental quality could predict individual differences in irregular past-tense performance (see Table 2). This is a demonstration that the characteristics of a population may dissociate with respect to development (mean performance) and individual differences (variation).

Although empirical data cannot yet speak directly to the existence of a Regularity $\times$ SES interaction, there are suggestive data. Bishop's original data set comprised 224 MZ and 218 DZ twins (Bishop, 2005). For that data set, the correlation between regular past-tense performance of MZ twins and DZ twins was .67 and .12, respectively; for irregulars, the MZ correlation was .45 and the DZ correlation .42 (Thomas et al., 2012). A behavioral genetic anal-

[3] For example, we trained Karaminis and Thomas's (2010) multiple inflection generator model on just the English past tense or simultaneously on multiple inflections for English verbs, nouns, and adjectives. At a point in training matched on vowel-change irregular verbs at 40% accuracy, the multiple-inflection model had regular verb accuracy levels 20% higher than the past-tense-only model.

ysis points to a greater contribution of environmental variation to individual differences in irregular verb performance than regular verb performance. One way to produce such a difference would be if the range of variation in the environmental input were wider for irregular verbs than regular verbs. That said, as we have seen, systematicity in regular verbs means that environmental variation has less effect on their development: Systematicity may exaggerate estimates of heritability.

Novel Predictions

The model produced four predictions. The first was testable against the Bishop (2005) data set. It was that SES would reliably predict whether a child was performing in the top 10% of the population, but not whether a child was performing in the bottom 10% of the population (see below). To our knowledge, this prediction has not been made by any existing theory of individual differences. The Bishop data set confirmed this prediction, providing a powerful validation of the model even in its qualitative form.

Second, the model predicted that where environment is the limiting factor on performance, SES effects should increase across development. This remains to be tested against longitudinal past-tense data. Such data would need to ensure the widest range of environmental variation possible, and exclude children with heritable language disorders, to narrow genetic range. In a recent longitudinal study, Tucker-Drob, Rhemtulla, Harden, Turkheimer, and Fask (2011) reported that in a sample of 750 twin pairs, SES was not related to mental ability at 10 months but was present at 2 years of age. When Petrill et al. (2004) tested expressive vocabulary and grammatical complexity via parental report in children at age 3 and then again at age 4 in a sample of 6,000–8,000 twins, SES effects were more consistent, predicting 3.2% and 3.6% of the variance at the two ages, respectively.

Third, given that SES might either modulate input or act on the computational properties of the learning system, we addressed whether these two pathways would generate different markers on behavioral variability. The model predicted that variation in the computational properties of the learning system might be more closely linked to generalization than to performance on the training set. A comparison of the ability of SES to predict variability in performance on children's knowledge (training set) versus extension of that knowledge to novel forms (generalization) may be one way to untangle whether the SES effects operate via the information content of the environment or via influencing the properties of the learning system itself.

Fourth, we investigated whether the model predicted that the effect of SES would operate differently at different levels of ability. (Where differences in ability stem from genetic factors, this would correspond to a gene–environment interaction.) We were particularly interested in whether the model predicted *resilience effects*, that is, high SES protecting against the effects of low ability, or high ability protecting against the effects of low SES. When we manipulated SES via input, and measured ability by the contribution of computational learning parameters to variation in performance, we did not find a resilience relationship. Low SES compressed variation due to ability, and low ability compressed the variation due to SES. The model predicted that SES effects would be highest in high-ability children and that these differences would increase across development. This condition gave another perspective on why SES has a higher predictive power on good performance than on poor performance, reflected in the divergence of SES trajectories for the high-ability group.

Was it possible for the model to capture resilience relationships between SES and ability? If SES and intrinsic influences both operate on computational learning properties, depending on which properties are involved, resilience relationships can be observed. But these have to involve a redundancy relationship, where the conferred advantage (of SES or ability) offers alternative pathways to buffer against variations in the other.

Insight Into Inferences From Behavior to Mechanism

Using a sample of 20 children, Rice et al. (1998) reported that SES (as measured by maternal education) did not reliably predict past-tense performance, explaining less than 1% of the variance. They inferred that the development of this aspect of morphosyntax was best explained in terms of maturational mechanisms, where changes in behavior over time are due to the aging process rather than experience dependent learning. The logic was that if development is not sensitive to variations in the environment, then developmental mechanisms cannot be relying on the environment. For the Bishop (2005) data set, SES similarly predicted only around 1% of the variance in regular past-tense performance, supporting the Rice et al. result. In our simulations, the condition that combined narrow variation in the information content of the environment with wide variation in the computational properties of the learning system also reproduced the result that the SES proxy predicted around 1% of the variance in past-tense performance. Crucially, however, the simulations demonstrate that Rice et al.'s inference about developmental mechanisms is not sound. This is because development in the connectionist model was entirely experience dependent and not at all maturational. Without exposure to the training set, no network would have learned anything. The lesson from the model is that caution must be exercised in drawing inferences about developmental mechanisms based on data from individual differences. The failure of measures of environmental variation to predict individual differences does not legitimize conclusions about the role of the environment in the developmental process.

As for the predictions, the model predicted that there should be no statistical relation between SES and whether a child fell in the bottom 10% of the population on past-tense formation, and this was confirmed in the empirical data. However, because the operation of the model is well understood, we can see that this result is a fairly curious one. We know that for the model, a poor environment *does cause* poor acquisition: The same model exposed to a poorer training set will learn less. We have here a divergence between statistical relations and causal relations. Unlike the more familiar case of *correlation without causation*, here we have *causation without correlation*. Poor environment causes poor development, but poor environment does not predict poor development. How can this be? The reason for the divergence is that the relationship of cause to effect was many to one. In addition to an impoverished environment, there were many other possible causes of poor acquisition, resulting from the settings of computational parameters. The many-to-one causal relationship diluted the strength of the statistical association of any one cause. By contrast, both parameters and environment had to be good for a network to feature in the top 10%; whether or not the environment was good then had stronger predictive power. In a population with largely adequate computational parameters, the nature of the environment should be a more symmetrical predictor of success and failure, and this was confirmed by simulation of such a population (see Table 3, IN-EW condition). The asymmetry was therefore predicted to be sensitive to the sampling. This is a further indication that in the actual data, variations in learning ability were a stronger determinant of individual differences than environmental variation in information. The model, then, demonstrates that many-to-one causal relations may compromise the window that statistical associations offer on causal mechanism.

Future Challenges for Investigating SES Through Computational Modeling

Our model needs to be extended in two ways: scaling up the complexity of the model and constraining the transform of the input due to SES by corpus-based analyses of child-directed speech. More widely, one key issue for future models to address is why SES effects should differ across different domains of cognition; for example, within language, why SES effects should be larger for vocabulary acquisition and phonological awareness than for grammar. Computational models exist that have been applied to the acquisition of phonology, to lexical segmentation, and to the acquisition of vocabulary (Davis, 2003; Plaut & Kello, 1999). Scaling these to population-level modeling would allow investigation of this issue. Once again, a central concern is to empirically constrain the variation in the language input and investigate how such variation interacts with differences in the computational properties of learning systems. The current simulations suggest that the input for phonology and vocabulary must be more variable than that for grammar; or the population range of computational properties generally more adequate; or that the problem domains of phonology and vocabulary are generally less systematic than the domain of grammar.

In addition to gene–environment interactions, the population-level modeling framework readily lends itself to considering gene–environment correlations, where certain genotypes are more often associated with certain environments. In our framework, this would be implemented as a correlation between the training set a system receives and the settings of its computational parameters (in our simulations, so far these were independent). Some groundwork has been completed in the field of language acquisition. In an artificial neural network model of English verb morphology, Hare and Elman (1995) demonstrated how training sets could become related to network properties, if what is learned by one generation is allowed to shape the training set of the next generation. At a population level, this scheme would allow investigation of the idea that genetic variations in learning ability could become correlated within environmental variations.

One complication of studying SES is that causal pathways through which it operates may alter across development, and indeed may depend on the range of SES under consideration. For example, Aikens and Barbarin (2008) found that family characteristics predicted more of the SES-linked variability in initial reading ability in kindergarten children, but for older children, school and neighborhood conditions explained more in subsequent improvements in reading through to third grade. In the developed world, even in the face of relative poverty, there is some minimal provision for the healthy upbringing of children. From the point of view of cognitive development, environmental variation may impact more on the information available and on the particular schedules of reward and punishment experienced by a child. However, in the developing world, the environmental range is much wider. Nutritional deficits during child development can be severe enough to cause stunting in growth and a statistically associated incidence of poor cognitive development (Grantham-McGregor et al., 2007). In this wider range, environmental variation may impact much more on biological aspects of neural function and therefore its computational properties.

Finally, we reiterate the focus of this article on the causal mechanisms by which SES effects operate. Research in this field is challenged by the many confounded factors associated with SES. They may all play a causal role, or some may be noncausal correlations. Computational modeling permits consideration of the adequacy of specific factors to explain behavioral data, but of course does not demonstrate that these mechanisms are truly responsible. For this, intervention studies are required. The potential reward of understanding causal pathways is that although the confounded factors may be many, if the causal pathways are few, then alleviating the effects of poverty on cognitive development may be easier than the alleviating poverty itself.

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