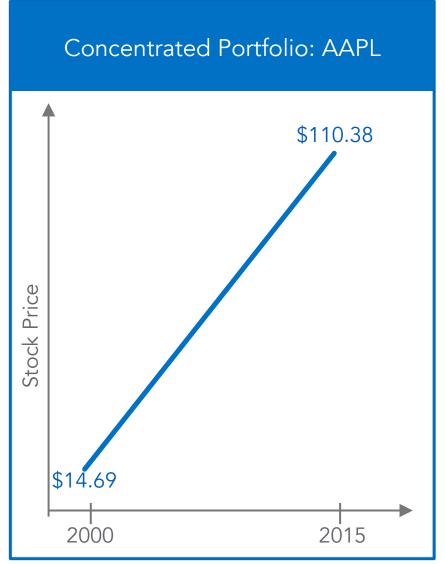
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Big Math For Big Problems

Predicting Predictions: The Use of Bayesian Model Averaging To Select Models

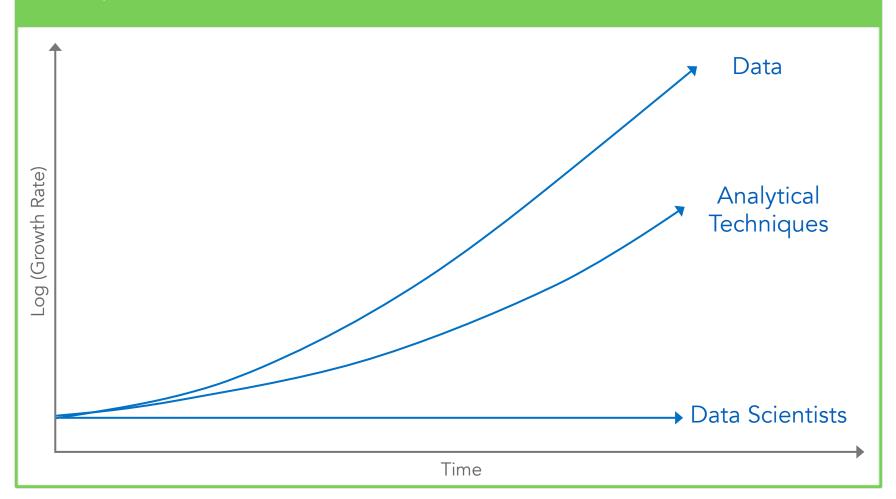








Explosive growth in digital data is driving a search for better software models.



24 June 2015

Data Grows In Two Ways



Long Data

	Α	В	C	D
	Individual	Number of		
	Sales made	Items in		
1	in Store B	Sale	Specific Items Sold	Date
2	\$235.90	6	4, 11, 25, 75, 13, 2	1/15/13
3	\$25.00	1	18	1/15/13
4	\$260.00	7	13, 2, 18, 111, 5, 1, 215	1/15/1
5	\$210.00	5	71, 9, 41, 69, 23	1/15/1
6	\$190.00	5	72, 35, 11, 12, 34	1/15/1
7	\$27.00	1	37	1/15/1
8	\$240.00	6	7, 13, 25, 75, 13, 2	1/15/1
9	\$22.00	1	56	1/15/1
10	\$21.00	1	72	1/15/1
11	\$250.00	6	4, 11, 25, 75, 13, 2	1/15/1
12	\$25.50	1	51	1/15/1
13	\$250.55	6	1, 23, 22, 75, 13, 2	1/15/1
14	\$52.00	1	17	1/15/1
15	\$52.40	1	72	1/15/1
16	\$261.00	7	75, 2, 18, 111, 5, 1, 215	1/15/1
17	\$271.20	7	111, 5, 1, 215, 75, 13, 2	1/15/1
18	\$25.00	1	72	1/15/1
19	\$70.77	2	67, 89	1/15/1
20	\$250.00	6	4, 11, 25, 75, 13, 2	1/15/1
21	\$78.00	2	31, 95	1/15/1
22	\$210.00	5	71, 9, 41, 69, 23	1/15/1
23	\$190.00	5	72, 35, 11, 12, 34	1/15/1
24	\$54.00	1	72	1/15/1
25	\$72.00	2	45, 23	1/15/1
26	\$220.00	6	10, 3, 29, 51, 13, 2	1/15/1
27	\$21,0.00	, 5	71, 9, 41, 69, 23	1/15/1
29	\$7 90		1, 25 5, 13	1/ 11

Rows

Wide Data

_	Α	В	С	D	E	F	G	H	I	J	K
									Reps in		
				Inventory	Size of Store	Operation		Peak	Store at	POS	Location
1	Store	Total Sales	Location	Total (units)	(sq. ft.)	Hours	Days Store is Open	Hours	Peek Hours	System	Specs
2	Α	\$2,359,000	City 1	786333	43685	9 - 9	M, T, W, Th, F, S, S	12 - 7	6	2012	Strip M
3	В	\$250,000	City 2	83333	4630	10 - 6	M, W, Th, F	2 - 4	1	2000	Stand Alo
4	С	\$2,600,000	City 3	866667	48148	9 - 9	M, T, W, Th, F, S, S	12 - 7	4	2012	Mall
5	D	\$2,100,000	City 4	700000	38889	9-9	M, T, W, Th, F, S, S	2 - 4	2	2000	Mall <
6	E	\$1,900,000	City 5	633333	35185	9-9	M, T, W, Th, F, S, S	12 - 7	8	2012	Mall
7	F	\$270,000	City 6	90000	5000	10 - 6	M, W, Th, F	2 - 4	1	2000	Strip Mall
8	G	\$2,400,000	City 7	800000	44444	9 - 9	M, T, W, Th, F, S, S	12 - 7	4	2012	Stand A
9	Н	\$220,000	City 8	73333	4074	10 - 6	M, W, Th, F	1-3	2	2000	Stand Alo
10	I	\$210,000	City 9	70000	3889	10 - 6	M, W, Th, F	1-3	3	2000	Stand Ale
11	J	\$2,500,000	City 10	833333	46296	9-9	M, T, W, Th, F, S, S	12 - 7	7	2012	Stand A
12	K	\$255,000	City 11	85000	4722	10 - 6	M, W, Th, F	1-3	5	2000	Strip Mall
13	L	\$2,505,500	City 12	835167	46398	9-9	M, T, W, Th, F, S, S	1-5	6	2000	Strip Ma
14	М	\$520,000	-	173333	9630	10 - 6	M, W, Th, F	2 - 4	6		Mall
15	N	\$524,000	-	174667	9704	10 - 6	M, W, Th, F	1-3	6	2000	Mall
16	0	\$2,610,000		870000	48333	9-9	M, T, W, Th, F, S, S	12 - 7	1	2000	Strip M
17	Р	\$2,712,000		904000	50222	9-9		1-5	7		Stand Alo
18	Q	\$250,000		83333	4630	10 - 6	M, W, Th, F	2 - 4			Stand Alo
19	R	\$707,700		235900			M, T, W, Th, F, S, S	1-5			Strip M
20		\$2,500,000		833333	46296	9-9		12 - 7			Strip Mali

Variables

Implications Of Wide Data



As the width of a data set grows, the number of possible relationships among the variables grows super-exponentially.

10 variables = 1,024 possible models



~large jar of jelly beans

Common problems with a small number of variables like retail sales predictions

100 variables >1 x 10^{29} possible models



> grains of sand on Earth

Rare events, like a power plant failure or a security breach 1,000 variables = nearly infinite models

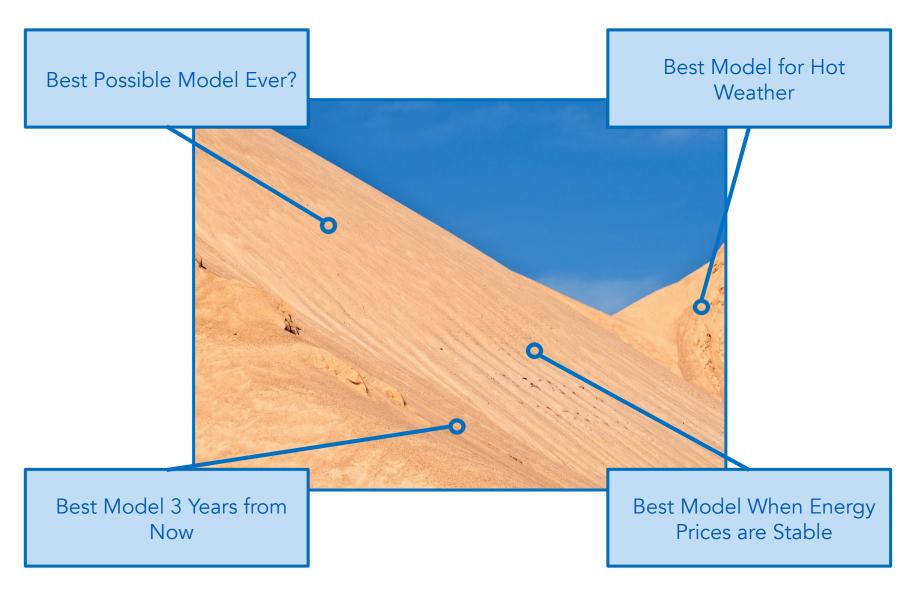


> all the atoms in the universe

Crop genetics problems routinely have 10,000+ variables

Diversification Mitigates Risk

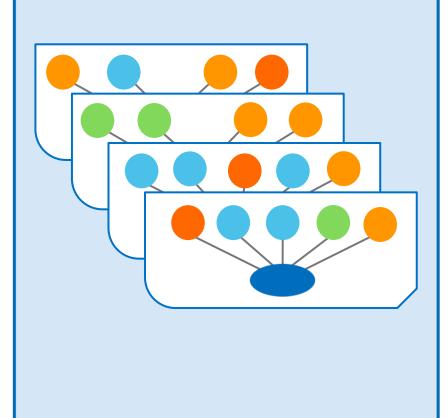




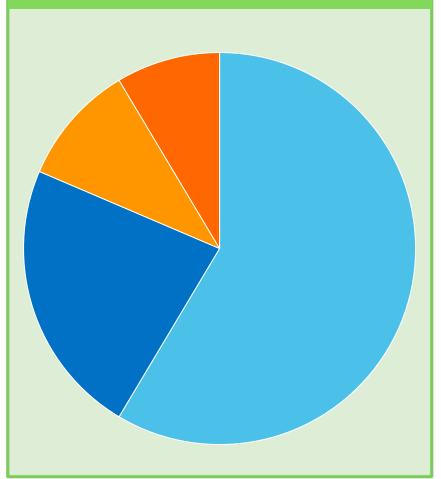
Ensemble vs. Portfolio Diversification



Ensemble: Same data sources with same analytical approach



Portfolio: Diverse data sources and diverse analytical approaches



The Catch



Common Issues In Portfolio Management

Correlation / Co-Linearity

Negative Weights Hypothesis Bias

Proposed Solution



The combination of advanced machine learning and Bayesian networks can address common portfolio issues.

Mathematics

Traditional Statistics

Bayesian Networks

Example Of Portfolio Of Models



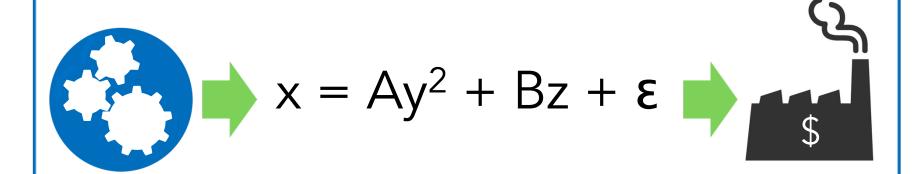
A portfolio would track performance against important scenarios.

	A	В	С	D	E
1	Model 1	Model 2	Model n	Weather	Energy Price
2					
3					
4					
5					
6					
7					
8					
9					
10					
11					
12					
13					
14					
15					
16 17					
18					
19					
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21					
22					
23					
74	\wedge \wedge \wedge		$\wedge \wedge \wedge \wedge \wedge$	\ \ \ \ \ \	

Beyond Algorithms



Ideally, our learning regarding algorithm performance goes beyond predictive performance but also measures outcomes from interventions.



The Benefits For Big Problems



A portfolio approach to software modeling is worth the effort when done well.

- Risk management
- Rigor and scale with which models can be compared
- Ability to integrate latest algorithmic advances
- Closed loop learning



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Colin Gounden

cgounden@viascience.com

Jeremy Taylor

jtaylor@viascience.com