Can Machines Learn Finance?

Bryan Kelly

Yale University and AQR Capital Management

* AQR Capital Management is a global investment management firm, which may or may not apply similar investment techniques or methods of analysis as described herein. The views expressed here are those of the authors and not necessarily those of AQR.

Machine Learning Works!

“Deep” neural networks have achieved
what was once unimaginable

Machine Learning Works!

1997 Deep Blue beats Kasparov

Machine Learning Works!

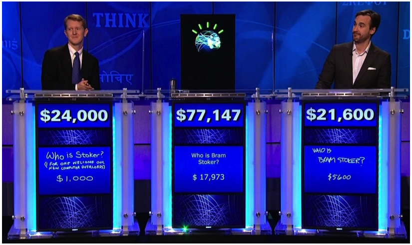
1997 Deep Blue beats Kasparov
2009 Google self-driving car

Machine Learning Works!

1997 Deep Blue beats Kasparov

2009 Google self-driving car

2011 Watson wins Jeopardy!



Machine Learning Works!

- 1997 Deep Blue beats Kasparov
- 2009 Google self-driving car
- 2011 Watson wins Jeopardy!
- 2012 Microsoft translates English to Chinese in real time

Machine Learning Works!

1997 Deep Blue beats Kasparov
2009 Google self-driving car
2011 Watson wins Jeopardy!
2012 Microsoft translates English to Chinese in real time
2016 AlphaGo beats Lee Sedol

Machine Learning Works!

1997 Deep Blue beats Kasparov

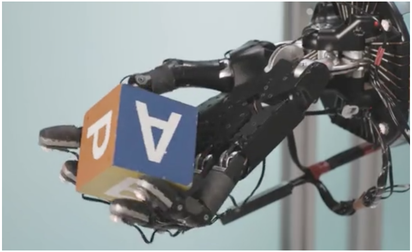
2009 Google self-driving car

2011 Watson wins Jeopardy!

2012 Microsoft translates English to Chinese in real time

2016 AlphaGo beats Lee Sedol

2018 OpenAI's "Dactyl" learns to manipulate objects



Can Machines Learn Finance?

Machines seem capable of anything...

- Speech recognition, translation, driving, juggling

... but can they learn finance?

Can Machines Learn Finance?

Machines seem capable of anything...

- Speech recognition, translation, driving, juggling

... but can they learn finance?

Finance is DIFFERENT

- Low signal-to-noise ratios
- Non-stationary, evolving markets
- Competition

Can Machines Learn Finance?

Machines seem capable of anything...

- Speech recognition, translation, driving, juggling

... but can they learn finance?

Finance is DIFFERENT

- Low signal-to-noise ratios
- Non-stationary, evolving markets
- Competition

Market Efficiency: Returns must be dominated by news in well functioning markets

Low signal-to-noise ratios are not a coincidence ...market efficiency reinforces it!

“Empirical Asset Pricing via Machine Learning”

Shihao Gu
Chicago Booth

Bryan Kelly
Yale and AQR

Dacheng Xiu
Chicago Booth

What We Do

- Comparative analysis of machine learning methods in context of perhaps most widely studied problem in finance, measuring equity risk premia

Our View: Best way to understand the relevance of ML for AP is to apply methods and compare performance in familiar empirical problem

Primary Contributions

1. Machine learning is economically meaningful
2. Machine learning ideally suited to asset pricing
3. New benchmark of accuracy in measuring risk premia

The (Very Familiar) Empirical Setting

$\sim$100 stock characteristics (usual suspects)

$+$

$\sim$10 macroeconomic predictors (a là Goyal-Welch)

$\Downarrow$

Monthly returns on 1) individual stocks and 2) stock portfolios

Which Machine Learning Methods?

- Linear Models
  - OLS(3) includes value, size, and 1-month reversal
  - OLS + Elastic Net + Huber's Loss
- Dimension Reduction: PCA, PLS
- Generalized Linear Models
  - Series Regression + Group Lasso
- Regression Trees
  - Random Forest
  - Gradient Boosted Regression Trees
- Deep Neural Networks
  - up to 5 hidden layers
  - around 30,000 parameters

Main Empirical Findings

Machine learning holds promise for empirical asset pricing

1. Non-linearities and interactions substantially improve predictions
2. Shallow learning outperforms deeper learning
3. Distance between non-linear methods and benchmark widens when predicting portfolios
4. Gains from machine learning forecasts are economically large
5. Most successful predictors: price trends, liquidity, and volatility

“Bottom-up” Prediction of (Pre-specified) Portfolios

Monthly Out-of-Sample R^2

	OLS-3	PLS	PCR	ENet	GLM	RF	GBRT	NN1	NN2	NN3	NN4	NN5
S&P 500	-0.11	-0.86	-2.62	-0.38	0.86	1.39	1.13	0.84	0.96	1.80	1.46	1.60
Big Growth	0.41	0.75	-0.77	-1.55	0.73	0.99	0.80	0.70	0.32	1.67	1.42	1.40
Big Value	-1.05	-1.88	-3.14	-0.03	0.70	1.41	1.04	0.78	1.20	1.57	1.17	1.42
Small Growth	0.35	1.54	0.72	-0.03	0.95	0.54	0.62	1.68	1.26	1.48	1.53	1.44
Small Value	-0.06	0.40	-0.12	-0.57	0.02	0.71	0.90	0.00	0.47	0.46	0.41	0.53
Big Conservative	-0.24	-0.17	-1.97	0.19	0.69	0.96	0.78	1.08	0.67	1.68	1.46	1.56
Big Aggressive	-0.12	-0.77	-2.00	-0.91	0.68	1.83	1.45	1.14	1.65	1.87	1.55	1.69
Small Conservative	0.02	0.75	0.48	-0.46	0.55	0.59	0.60	0.94	0.91	0.93	0.99	0.88
Small Aggressive	0.14	0.97	0.06	-0.54	0.19	0.86	1.04	0.25	0.66	0.75	0.67	0.79
Big Robust	-0.58	-0.22	-2.89	-0.27	1.54	1.41	0.70	0.60	0.84	1.14	1.05	1.21
Big Weak	-0.24	-1.47	-1.95	-0.40	-0.26	0.67	0.83	0.24	0.60	1.21	0.95	1.07
Small Robust	-0.77	0.77	0.18	-0.32	0.41	0.27	-0.06	-0.06	-0.02	0.06	0.13	0.15
Small Weak	0.02	0.32	-0.28	-0.25	0.17	0.90	1.31	0.84	0.85	1.09	0.96	1.08
Big Up	-1.53	-2.54	-3.93	-0.21	0.40	1.12	0.68	0.46	0.85	1.28	0.99	1.05
Big Down	-0.10	-1.20	-2.05	-0.26	0.36	1.09	0.77	0.48	0.89	1.34	1.17	1.36
Small Up	-0.79	0.42	-0.36	-0.33	-0.33	0.31	0.40	0.23	0.60	0.67	0.55	0.61
Small Down	0.40	1.16	0.47	-0.46	0.62	0.93	1.20	0.80	0.97	0.97	0.97	0.96

“Bottom-up” Prediction of (Pre-specified) Portfolios

Timing Sharpe Ratio Improvement Over Buy/Hold

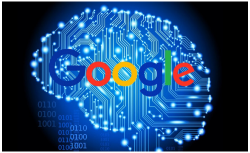
	OLS-3	PLS	PCR	ENet	GLM	RF	GBRT	NN1	NN2	NN3	NN4	NN5
S&P 500	-	-	-	-	0.11	0.17	0.14	0.11	0.12	0.21	0.17	0.19
Big Growth	0.05	0.09	-	-	0.08	0.11	0.09	0.08	0.04	0.18	0.15	0.15
Big Value	-	-	-	-	0.10	0.19	0.15	0.12	0.17	0.21	0.16	0.19
Small Growth	0.03	0.14	0.07	-	0.09	0.05	0.06	0.15	0.11	0.13	0.13	0.13
Small Value	-	0.08	-	-	0.00	0.14	0.17	0.00	0.10	0.09	0.09	0.11
Big Conservative	-	-	-	0.02	0.08	0.11	0.09	0.12	0.08	0.18	0.15	0.16
Big Aggressive	-	-	-	-	0.11	0.26	0.22	0.18	0.24	0.26	0.23	0.24
Small Conservative	0.00	0.08	0.05	-	0.06	0.06	0.07	0.10	0.10	0.10	0.11	0.09
Small Aggressive	0.03	0.15	0.01	-	0.04	0.14	0.16	0.05	0.11	0.12	0.11	0.13
Big Robust	-	-	-	-	0.17	0.16	0.08	0.07	0.10	0.13	0.12	0.14
Big Weak	-	-	-	-	-	0.12	0.14	0.05	0.11	0.19	0.16	0.17
Small Robust	-	0.08	0.02	-	0.04	0.03	-	-	-	0.01	0.01	0.02
Small Weak	0.00	0.06	-	-	0.03	0.16	0.21	0.15	0.15	0.18	0.16	0.18
Big Up	-	-	-	-	0.05	0.13	0.08	0.06	0.10	0.14	0.11	0.12
Big Down	-	-	-	-	0.06	0.15	0.11	0.07	0.13	0.18	0.16	0.18
Small Up	-	0.05	-	-	-	0.04	0.05	0.03	0.07	0.08	0.06	0.07
Small Down	0.07	0.17	0.08	-	0.10	0.15	0.18	0.13	0.15	0.15	0.15	0.15

Machine Learning Long-Short Portfolios

Value-weighted Portfolio Performance

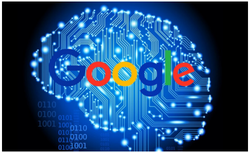
	OLS-3+H				PLS				PCR			
	Pred	Avg	Std	SR	Pred	Avg	Std	SR	Pred	Avg	Std	SR
Low	-0.42	0.39	5.22	0.26	-0.86	0.27	5.57	0.17	-0.90	0.04	5.92	0.03
2	-0.08	0.60	4.47	0.46	-0.27	0.49	5.10	0.33	-0.29	0.43	5.33	0.28
9	1.42	0.56	7.50	0.26	1.49	0.94	5.01	0.65	1.47	1.18	4.98	0.82
High	1.72	0.90	8.18	0.38	2.03	0.96	5.45	0.61	2.02	1.36	5.61	0.84
H-L	2.14	0.51	6.46	**0.27**	2.89	0.70	4.35	0.56	2.92	1.32	4.72	0.97
	ENet+H				GLM+H				RF			
Low	0.05	0.08	5.64	0.05	-0.42	0.11	5.43	0.07	0.28	0.09	6.09	0.05
2	0.33	0.52	5.07	0.35	0.02	0.46	4.67	0.34	0.41	0.39	5.17	0.26
9	1.33	0.88	5.59	0.55	1.36	0.97	5.49	0.61	0.89	1.20	5.88	0.70
High	1.59	0.80	6.83	0.40	1.76	1.18	6.30	0.65	1.01	1.49	7.18	0.72
H-L	1.54	0.72	5.49	0.45	2.17	1.08	4.52	0.83	0.73	1.40	5.54	0.87
	GBRT+H				NN1				NN2			
Low	0.00	0.03	5.76	0.02	-0.40	-0.37	7.16	-0.18	-0.30	-0.50	7.89	-0.22
2	0.16	0.50	5.00	0.34	0.15	0.40	6.03	0.23	0.18	0.36	6.13	0.21
9	0.81	0.99	5.08	0.67	1.60	0.94	5.09	0.64	1.40	1.01	5.52	0.63
High	0.97	1.20	5.81	0.71	2.18	1.37	6.31	0.75	2.03	1.43	6.95	0.72
H-L	0.97	1.16	4.27	0.94	2.58	1.73	5.62	1.07	2.32	1.94	5.68	1.18
	NN3				NN4				NN5			
Low	-0.21	-0.51	7.83	-0.23	-0.29	-0.43	7.74	-0.19	-0.15	-0.36	7.63	-0.16
2	0.26	0.32	6.39	0.18	0.20	0.39	6.15	0.22	0.26	0.29	6.36	0.16
9	1.28	1.20	5.79	0.72	1.36	1.07	5.87	0.63	1.26	1.31	5.77	0.79
High	1.99	1.58	7.33	0.74	2.02	1.47	7.11	0.72	1.91	1.55	6.90	0.78
H-L	2.20	2.09	5.78	**1.25**	2.30	1.90	5.83	1.13	2.06	1.91	6.01	1.10

Can Machines Learn Finance?



2011: Google Brain launches. Uncertain if deep neural networks would identify a cat, let alone drive a car

Can Machines Learn Finance?



2011: Google Brain launches. Uncertain if deep neural networks would identify a cat, let alone drive a car

Answer: Yes, but there is much more to learn

- Most <u>anecdotes</u> in low capacity settings (HFT, OTC, etc.)
- We provide first large scale evidence of value for long-term asset management
- These are early days (2011 cat recognition)