Enhancing Statistical Significance of Backtests

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About Me

- Previously, researcher at IBM T. J. Watson Lab in machine learning, researcher/trader for Morgan Stanley, Credit Suisse, and various hedge funds.
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- Author:
  - *Machine Trading: Deploying Computer Algorithms to Conquer the Markets* (Wiley 2017).
  - *Algorithmic Trading: Winning Strategies and Their Rationale* (Wiley 2013).
  - *Quantitative Trading: How to Build Your Own Algorithmic Trading Business* (Wiley 2009).
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Limitations of Financial Data

- Machine learning depends on training data with stable statistics
  - E.g. Facial recognition, speech recognition, playing GO.
- Financial data is anything but stable.
  - Regime changes regularly.
  - Anomalies disappearing due to increasing arbitrage activities.
  - In contrast, cats don’t change their faces because computers start to recognize them on YouTube.

Limitations of Financial Data

- Regime changes render older data unsuitable for testing new strategies.
  - 2001 Decimalization of stock prices.
  - 2008 Financial crisis and start of quantitative easing.
- Only about 2,000 rows of daily data since 2008.
  - Google (Le *et al*, 2012) used 10 million YouTube videos to train neural network to recognize cats' faces.

Limitations of Financial Data

- Seasonality further limits size of data sets.
  - Options expirations strategies rely on weekly or monthly data.
  - Earnings strategies rely on quarterly data.
  - Seasonal physical commodity futures strategies rely on annual cycles.

Overcoming Data Scarcity

- Use **high frequency** data
  - Arbitrage opportunities depend on time scale.
  - Inapplicable to strategies for longer time scales.
  - There is seasonality even intraday.
- **Aggregate** data from multiple instruments
  - E.g. run same trading model on all Russell 3,000 stocks.
  - 2,000 rows x 3,000 columns = 6 million data points.

Reducing Overfitting

- **Bagging**
  - Over-sampling existing data to create more rows.
- **Random Subspace**
  - Under-sampling existing predictors to limit overfitting.
- **Stepwise Regression**
  - Sequentially adding predictors, then sequentially removing predictors.
- **Random Forest**
  - Combining bagging and random subspace.

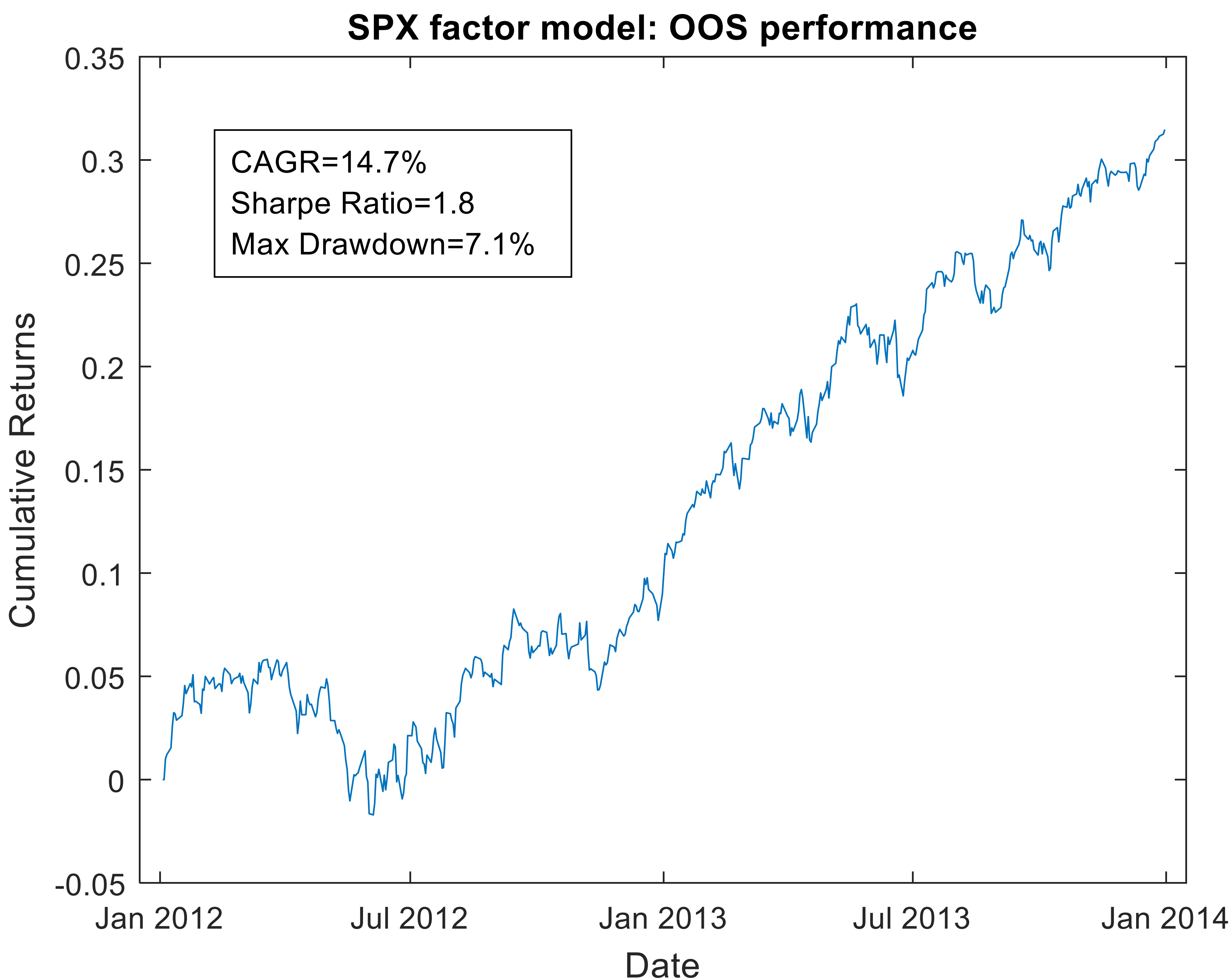
Example: Factor Model on SPX Stocks

- Predict quarterly returns on stocks using simple linear model:
$$Return(t+1,s) = \alpha + \beta_1(t,s) * Factor_1 + \beta_2(t,s) * Factor_2 + \cdots + \varepsilon(\mathrm{t},\mathrm{s})$$
- Use fundamental factor loadings $\beta_{\mathrm{i}}(t,s)$ extracted from quarterly financial statements as predictors.
- Restrict ourselves to factor loadings that do *not* scale with a firm's size.
  - There are about 27 such factor loadings.
  - Source: Sharadar's Core US Fundamentals database via Quandl.com.

Variable name	Explanation	Period
CURRENTRATIO		Quarterly
DE	Debt to Equity Ratio	Quarterly
DILUTIONRATIO	Share Dilution Ratio	Quarterly
PB	Price to Book Value	Quarterly
TBVPS	Tangible Asset Book Value per Share	Quarterly
ASSETTURNOVER		Trailing 1 Year
EBITDAMARGIN		Trailing 1 Year
EPSGROWTH1YR		Trailing 1 Year
EQUITYAVG	Average Equity	Trailing 1 Year
EVEBIT	Enterprise Value over EBIT	Trailing 1 Year
EVEBITDA	Enterprise Value over EBITDA	Trailing 1 Year
GROSSMARGIN		Trailing 1 Year
INTERESTBURDEN	Financial Leverage	Trailing 1 Year
LEVERAGERATIO		Trailing 1 Year
NCFOGROWTH1YR		Trailing 1 Year
NETINCGROWTH1YR	Net Income Growth	Trailing 1 Year
NETMARGIN	Profit Margin	Trailing 1 Year
PAYOUTRATIO		Trailing 1 Year
PE	Price Earnings Damodaran Method	Trailing 1 Year
PE1		Trailing 1 Year
PS		Trailing 1 Year
PS1	Price Sales Damodaran Method	Trailing 1 Year
REVENUEGROWTH1YR		Trailing 1 Year
ROA		Trailing 1 Year
ROE		Trailing 1 Year
ROS		Trailing 1 Year
TAXEFFICIENCY		Trailing 1 Year

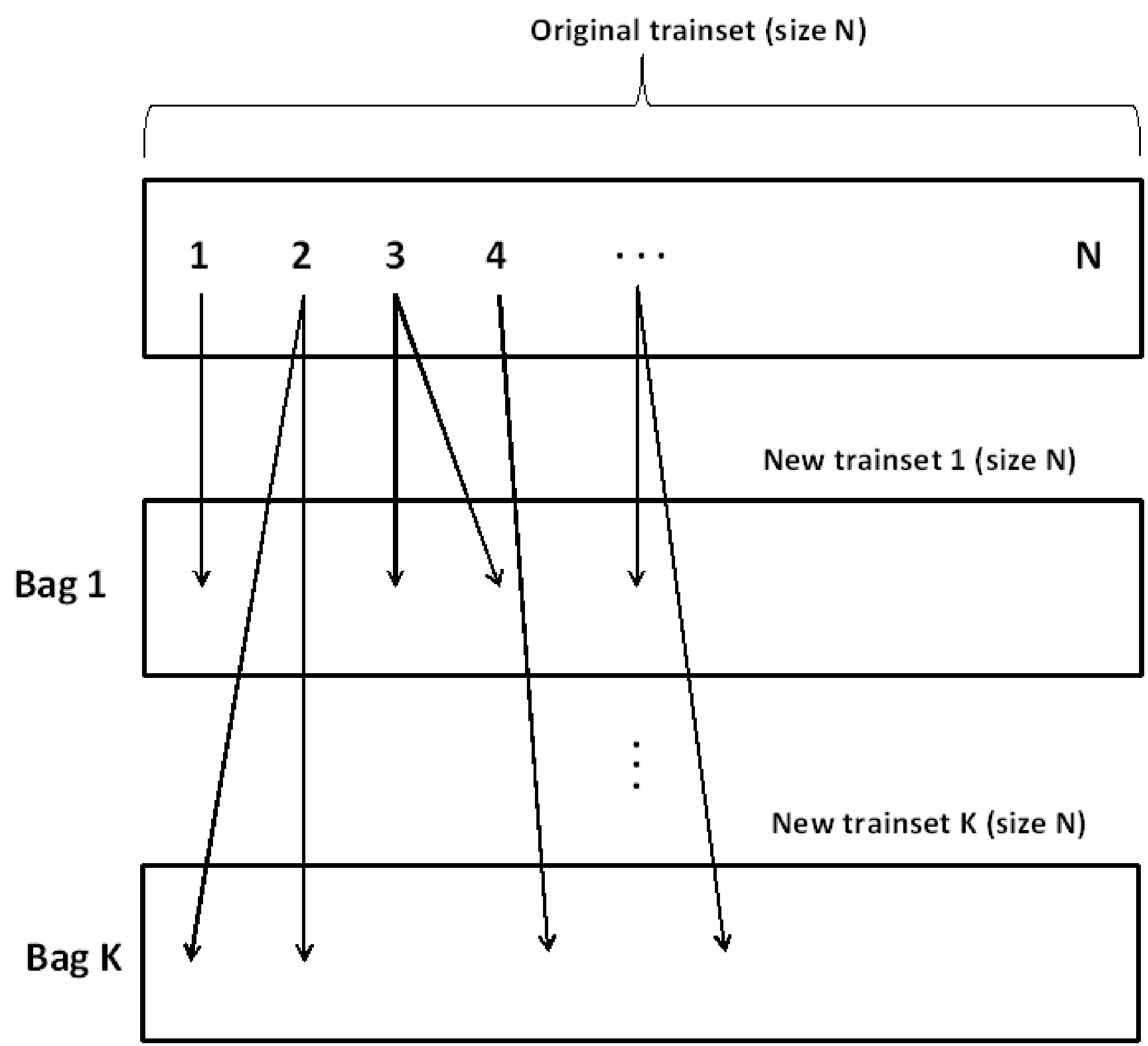
Factor Model on SPX Stocks

- $Factor_{\mathrm{i}}$ are the regression coefficients: assumed fixed across all *stocks* and all *time*.
  - **Aggregation** in action!
  - Training data: 200701-201112.
  - 1,260x 500 data points (instead of just 1,260).
- Trading strategy: At end of each day
  - Buy if predicted return > 0, *vice versa* for short.
  - Hold for a quarter.


SPX factor model: OOS performance
CAGR=14.7%
Sharpe Ratio=1.8
Max Drawdown=7.1%
Cumulative Returns
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
Jan 2012
Jul 2012
Jan 2013
Jul 2013
Jan 2014
Date

Bagging

- Increasing the training set (size *N*) by over-sampling data.
  - i.e. Resampling with replacement.
- Re-sample *N* data points to become *K* bags of *N* data points.
  - Total: *K* x *N* data points.
- Train separate model for each bag.
- Take average predicted returns of *K* models.


Original trainset (size N)
1
2
3
4
· · ·
N
New trainset 1 (size N)
Bag 1
New trainset K (size N)
Bag K

Random Subspace

- Randomly select subset of predictors to train *K* models.
- Similar to bagging, take average predicted returns of *K* models.

Random Forest

- Combine both bagging and random subspace:
  - Over-sample data
  - Under-sample* (in our case) predictors

*In other applications such as classification and regression trees, we can over-sample and re-use predictors too (*i.e.* sampling with replacement)

Out-of-Sample Results

	CAGR	Sharpe Ratio	Calmar Ratio
Base model (aggregated)	14.7%	1.8	2.1
Bagging (K=100)	15.1%	1.8	2.1
Random Forest (K=100, 14 predictors)	16.7%	1.7	2.1

Interpretation

- Glass half empty:
  - Random forest does not improve performance significantly.
- Glass half full:
  - Random forest shows that original performance is robust with respect to re-sampling.
  - I.e. original results are **statistically significant**!

Stepwise Regression

- Random subspace/forest randomly picking predictors.
- Stepwise regression picked them step-by-step based on BIC: essentially maximizing log-likelihood while penalizing number of variables.
  - BIC is proportional to negative log likelihood.
- Stop adding variables when BIC is minimized, then start deleting them until BIC increases.

Out-of-Sample Results

	CAGR	Sharpe Ratio	Calmar Ratio
Base model (aggregated)	14.7%	1.8	2.1
Bagging (K=100)	15.1%	1.8	2.1
Random Forest (K=100, 14 predictors)	16.7%	1.7	2.1
Stepwise Regression	19.1%	1.8	2.2

Stepwise Regression

- Just 2 variables generate all the predictive power of the factor model.
  - Gross margin (trailing 1 year)
  - Price-to-Sales (trailing 1 year)

- Similar result may be generated by “L1 regularization”?

Market Neutral Version

- Is good return due to a net long exposure during the bull market?
- Modified trading strategy:
  - Buy 50 stocks with the top predicted returns
  - Short 50 stocks with the bottom predicted returns
  - Hold for 1 quarter.
- Out-of-sample: CAGR=5.54%, Sharpe=1.4, Calmar=1.4.
- Model has real alpha!

Conclusion

- Aggregating data across time or instruments usually a good idea.
- Selectively reduction of variables produce slightly better results than oversampling training data.
- Reduction of variables produces a more parsimonious model with more intuitive meaning.

Thank you for your time!

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