



University of Toronto  
School of Continuing Studies  
3253 - Machine Learning

# Can factor investing disrupt the hedge fund industry?

Mirroring “Global Macro” Hedge Funds performance through factor-based predictive modelling and ensemble learning

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# Hedge Funds

- Wealthy individuals or institutional investors
- Significant diversification benefits
- “Absolute returns” (positive risk-adjusted returns)

**Has anyone invested in hedge funds before?**

Sources:

Edwards, F. R., & Gaon, S. (2003). Hedge Funds: What Do We Know? *Journal of Applied Corporate Finance*, 15(4), 58-71.  
Fung, W., & Hsieh, D. A. (1999). A primer on hedge funds. *Journal of Empirical Finance*, 6(1999), 309-331.



# US Global Macro Hedge Funds



3 trillion USD  
CAGR 8%-10%  
5-10 years



14,000 US firms  
Top fund uses global macro strat  
George Soros - \$1 billion overnight



Each of the top 35 US hedge funds >  
entire Canadian hedge funds industry  
(200 hedge funds, 200 billion in AUM)

Sources:

Banquier, S. (2019). Overview of Prime Brokerage. Presented at Smith School of Business, Queen's University.

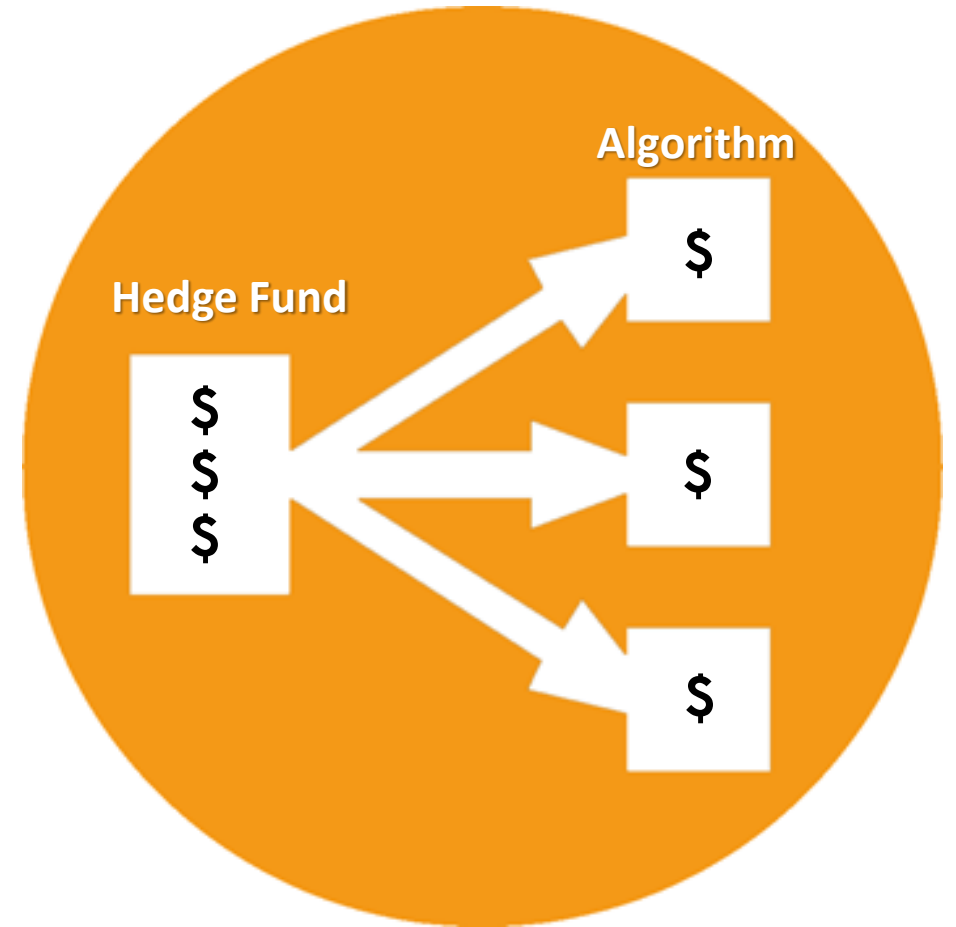
Fung, W., & Hsieh, D. A. (2011). The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds. *Journal of Empirical Finance*, 18(2011), 547-569.

# Research Question

***Are “Global Macro” Hedge Funds replicable using the factor-based frameworks for non-accredited investors (like you and me)?***

# Objectives

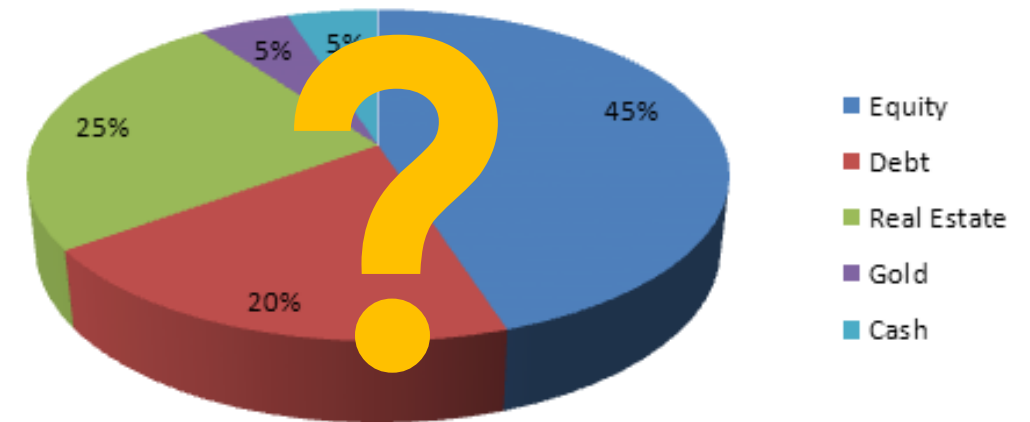
- **Dynamic linkages:** can market variables predict GMHF performance?
- **Neutrality:** or do dynamic investment strategies (i.e. manager skill) play a factor?
- **Implication:** systematically replicate results without Hedge Fund fees



# Methodology

- Gather and prepare the data – target variables and feature variables
- Predict the target using feature variables using machine learning
- Identify the best factor-based framework to replicate GMHF Performance
- Use feature selection to determine portfolio weightage per feature
- Inform non-accredited investors of index trackers to mirror GMHF returns

**Asset Allocation Example**



*How much \$ do you allocate per index or asset class to mirror the performance of a GMHF?*

# Data Exploration



**Target:** Global Macro  
Hedge Funds Mean Index  
Returns (GMHF)



**Fama-French-Carhart 4 Factor Model**  
Market returns (Mkt), size factor (SMB), value  
factor (HML) and momentum (MOM)



**Risk-based Factor Model**  
Bond Trending following risk factors  
Equity-oriented risk factors  
Bond-oriented risk factors

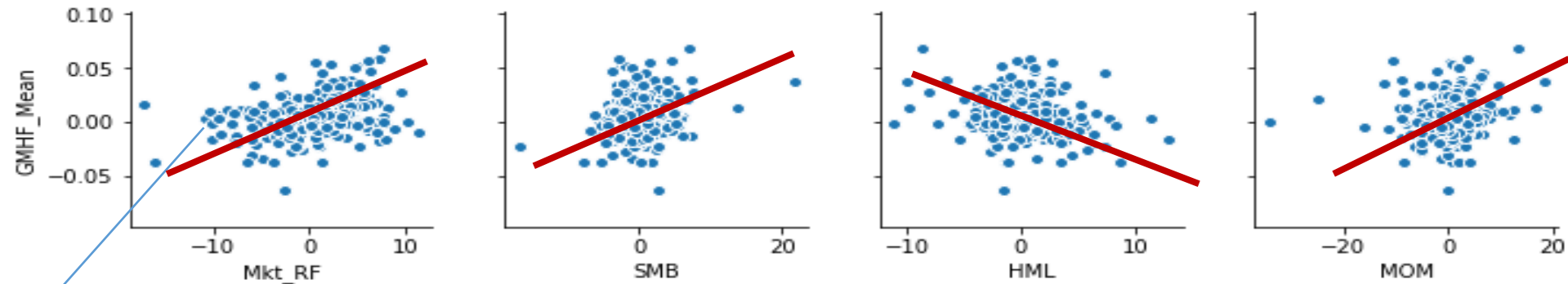


**Macroeconomic Factor Model**  
GDP, inflation rate, interest rates,  
unemployment rates, etc

**Observations:** 1994-2018, 300 monthly data points

**Source:** Hedge Fund Research Institute, Ken French Library, David Hsieh Library, US government data

# Data Exploration - 4 factor model



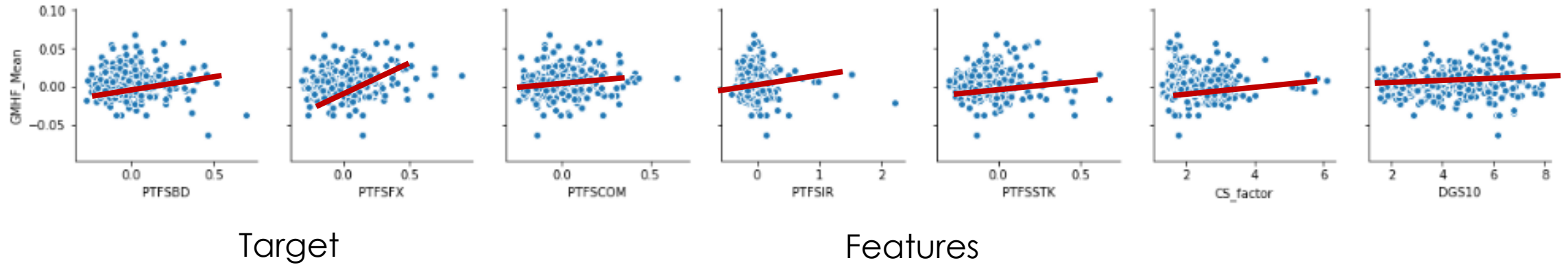
Target

Features

	GMHF_Mean	Mkt_RF	SMB	HML	MOM
count	300.000000	300.000000	300.000000	300.000000	300.000000
mean	0.005155	0.625467	0.112667	0.149233	0.431233
std	0.017692	4.296355	3.280816	3.026984	4.926031
min	-0.064000	-17.230000	-16.870000	-11.100000	-34.390000
25%	-0.005525	-1.960000	-1.972500	-1.442500	-1.300000
50%	0.003950	1.185000	0.025000	-0.060000	0.480000
75%	0.015100	3.377500	1.912500	1.682500	2.825000
max	0.068200	11.350000	21.710000	12.900000	18.360000

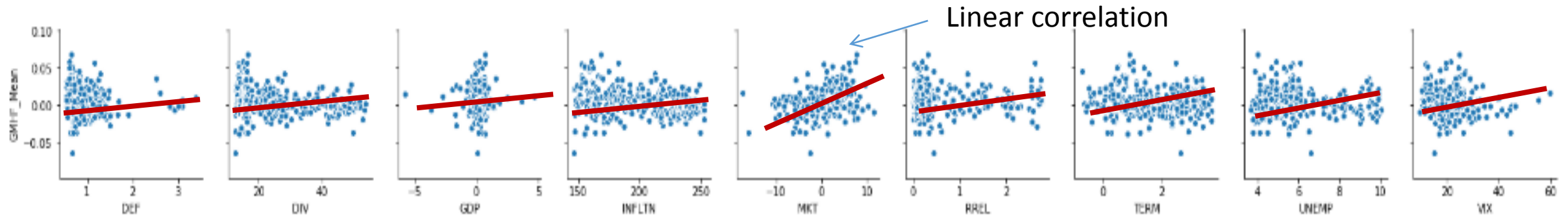


# Data Exploration – Risk Based Model



	GMHF_Mean	PTFSBD	PTFSFX	PTFSKOM	PTFSIR	PTFSSTK	CS_factor	DGS10
count	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000
mean	0.005155	-0.01890	-0.008167	-0.005833	-0.020800	-0.048400	2.421133	4.133867
std	0.017692	0.15202	0.193697	0.140519	0.249809	0.141559	0.786240	1.636767
min	-0.064000	-0.27000	-0.320000	-0.250000	-0.420000	-0.300000	1.300000	1.460000
25%	-0.005525	-0.13000	-0.150000	-0.100000	-0.140000	-0.150000	1.770000	2.667500
50%	0.003950	-0.05000	-0.050000	-0.030000	-0.070000	-0.070000	2.335000	4.095000
75%	0.015100	0.04000	0.082500	0.060000	0.040000	0.020000	2.860000	5.422500
max	0.068200	0.69000	0.900000	0.650000	2.220000	0.670000	6.100000	7.910000

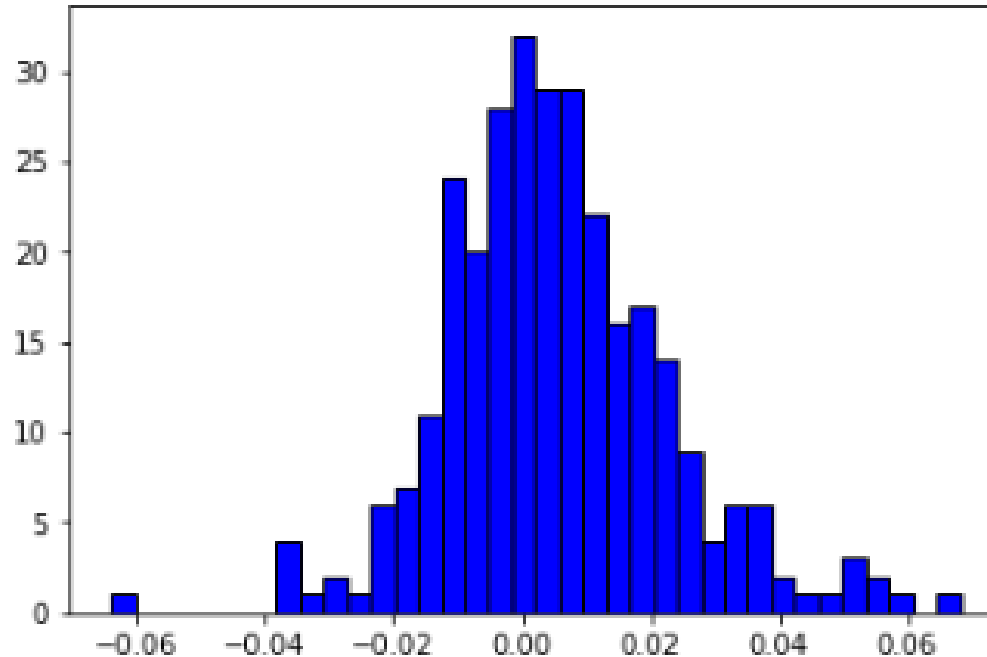
# Data Exploration – Macroeconomic Model



	GMHF_Mean	DEF	DIV	GDP	INFLTN	MKT	RREL	TERM	UNEMP	VIX
count	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000
mean	0.005155	0.958833	25.117967	0.150367	199.963367	0.625467	0.620500	1.701100	5.788000	19.699133
std	0.017692	0.415017	11.252852	0.720316	31.924226	4.296355	0.764919	1.090485	1.631193	7.668713
min	-0.064000	0.550000	12.620000	-5.800000	146.300000	-17.230000	0.000000	-0.700000	3.700000	9.510000
25%	-0.005525	0.690000	16.035000	-0.040000	170.975000	-1.960000	0.120000	0.882500	4.600000	13.870000
50%	0.003950	0.870000	22.230000	0.190000	201.850000	1.185000	0.280000	1.685000	5.400000	17.970000
75%	0.015100	1.072500	29.727500	0.342500	231.070000	3.377500	0.792500	2.602500	6.125000	23.662500
max	0.068200	3.380000	53.750000	4.710000	252.790000	11.350000	2.760000	3.680000	10.000000	59.890000

# Target : Global Macro Hedge Funds Mean Index Returns (GMHF)

GMHF_Mean	1.000000
Mkt_RF	0.343204
MKT	0.343204
PTFSFX	0.218802
SMB	0.203621
RF	0.176255
PTFSOOM	0.167985
DGS10	0.151699
MOM	0.148669
PTFSSTK	0.084910
RREL	0.080355
GDP	0.019099
PTFSBD	0.017395
DEF	-0.045166
PTFSIR	-0.061360
UNEMP	-0.063736
VIX	-0.089781
CS_factor	-0.090315
TERM	-0.093911
CMA	-0.148520
HML	-0.177371
DIV	-0.185010
INFLTN	-0.196122
RMW	-0.259977



Applied models	Hypothesis
regression	How much could the businessmen get in terms of ROI
classification	Could they gain or lose in their GMHF investment

# Model Building Process

Feature Selection	Numeric Variables
Fama-French-Carhart	'Mkt_RF','SMB','HML','MOM'
Risk-based	'PTFSBD','PTFSFX','PTFSCOM','PTFSIR','PTFSSTK','DGS10','CS_factor'
Macroeconomic	'DEF','DIV','GDP','INF','MKT','RREL','TERM','UNEMP','VIX'



Algorithms Comparison	Regression (RMSE)	Classification (Accuracy)
Linear Algorithms	LinearRegression	LogisticRegression
Non-Linear Algorithms	KNeighborsRegressor, SVR	KNeighborsClassifier, DecisionTreeClassifier, GaussianNB, SVC
Emsemble Algorithms	GradientBoostingRegressor, RandomForestRegressor	VotingClassifier, RandomForestClassifier



Making pipeline	1. Scaling   2. PCA   3. Parameters tuning (GridSearchCV) for the best algorithm
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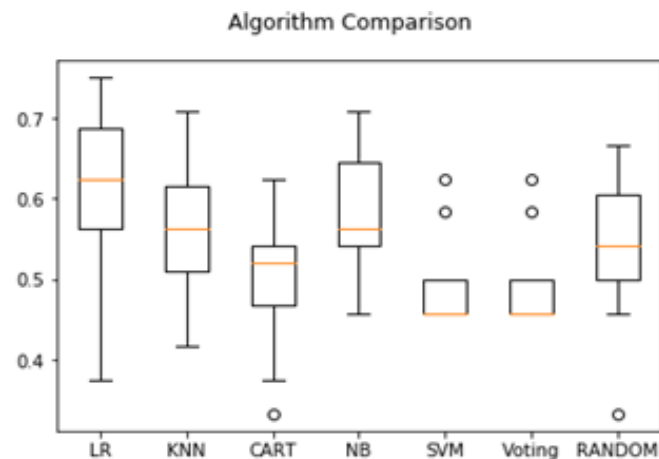


Feature Importance	Use Algorithm RandomForest method best_estimator.feature_importances
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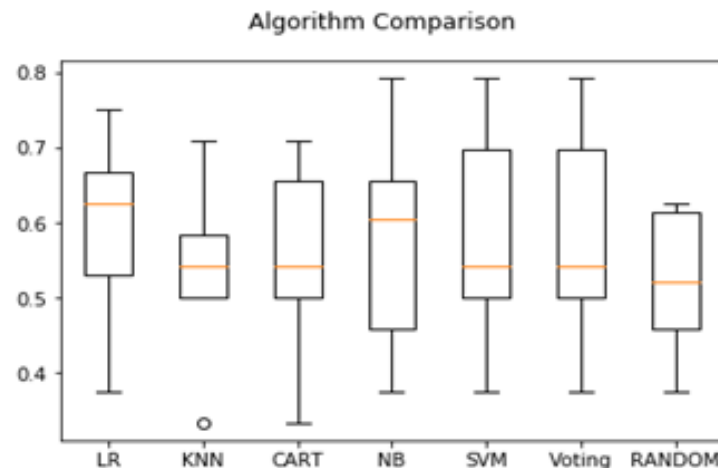


# Classification

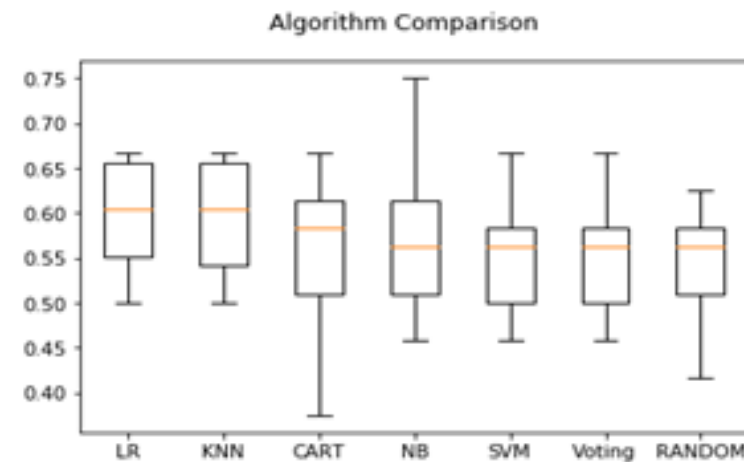
## Fama-French-Carhart



## Risk-based



## Macroeconomic



Best parameter (CV score=0.625):

`{'logistic_C': 35.564803062231285, 'logistic_penalty': 'l2', 'pca_n_components': 2}`

LG Model test Accuracy:: 0.6833333333333333

Best parameter (CV score=0.637):

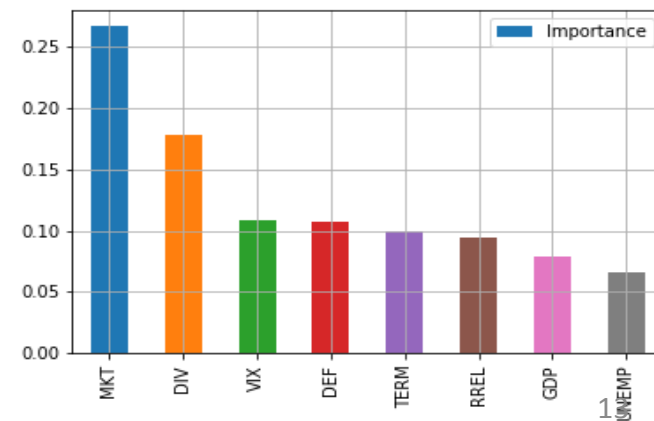
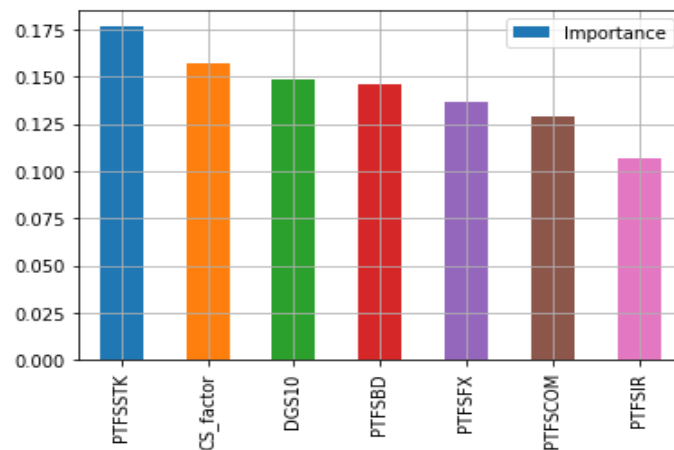
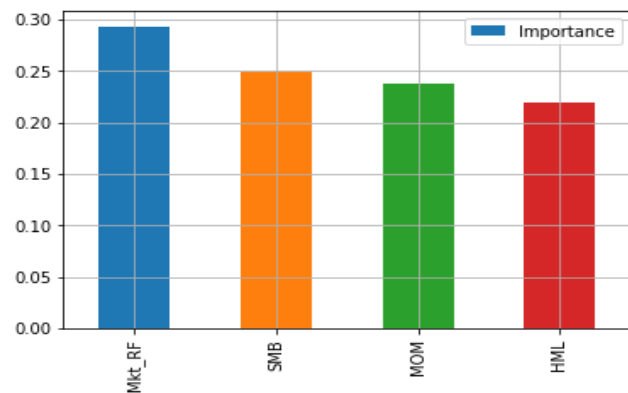
`{'logistic_C': 0.0001, 'logistic_penalty': 'l2', 'pca_n_components': 4}`

LG Model test Accuracy:: 0.7666666666666667

Best parameter (CV score=0.646):

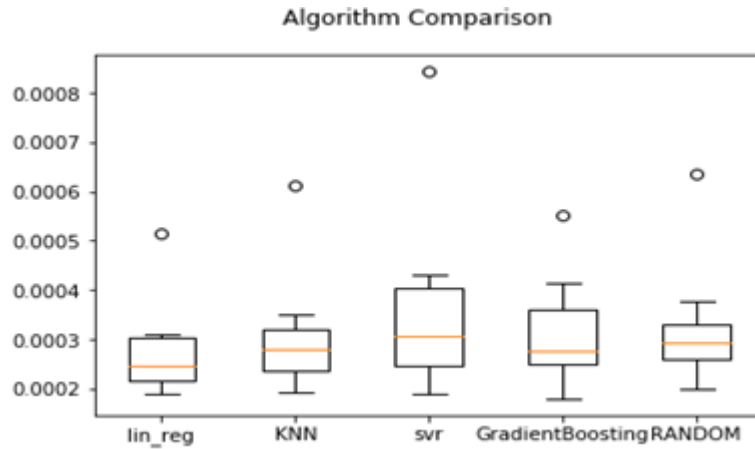
`{'logistic_C': 0.013257113655901081, 'logistic_penalty': 'l2', 'pca_n_components': 3}`

LG Model test Accuracy:: 0.6333333333333333



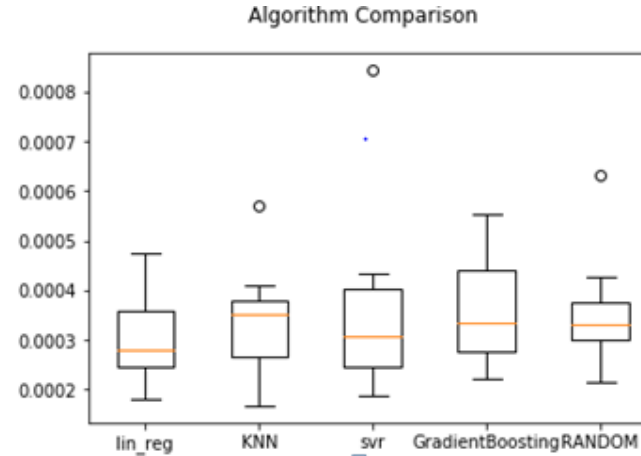
# Regression

## Fama-French-Carhart



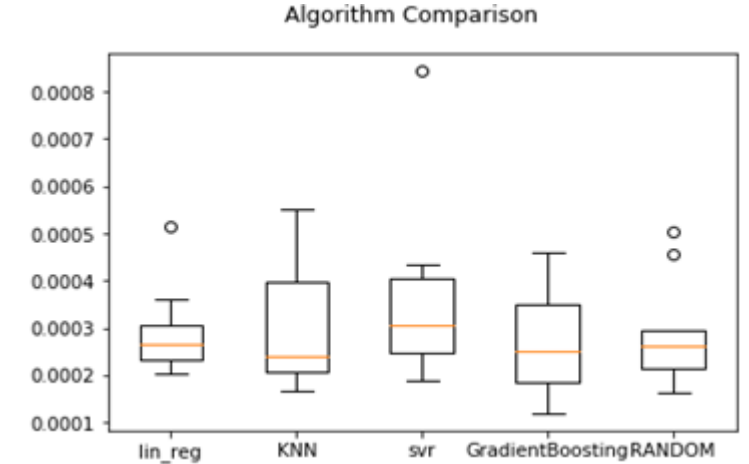
Best parameter (CV score=0.074):  
 {'pca\_n\_components': 4}  
 RSME Based On Linear Regression: 0.01536944488278775

## Risk-based

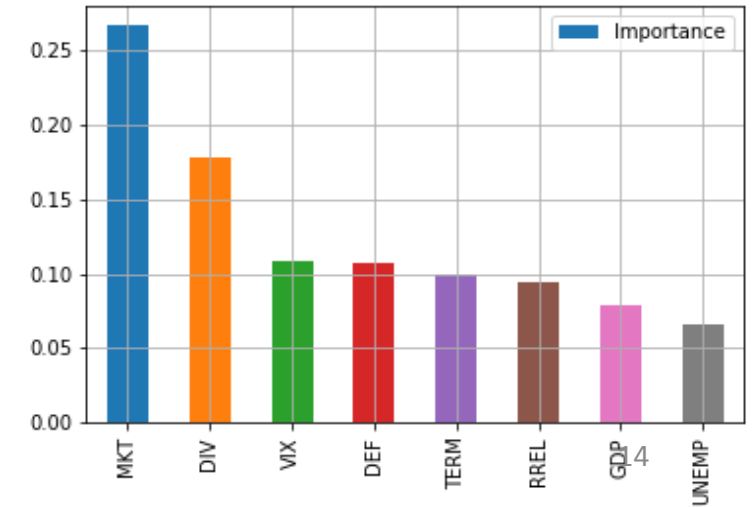
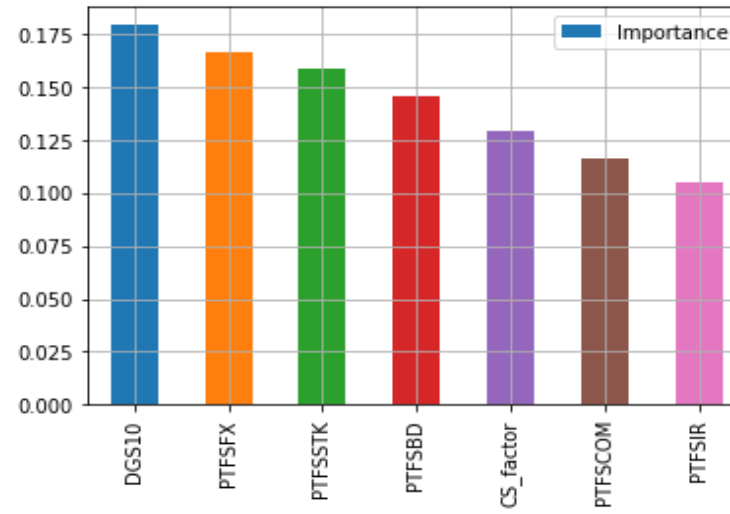
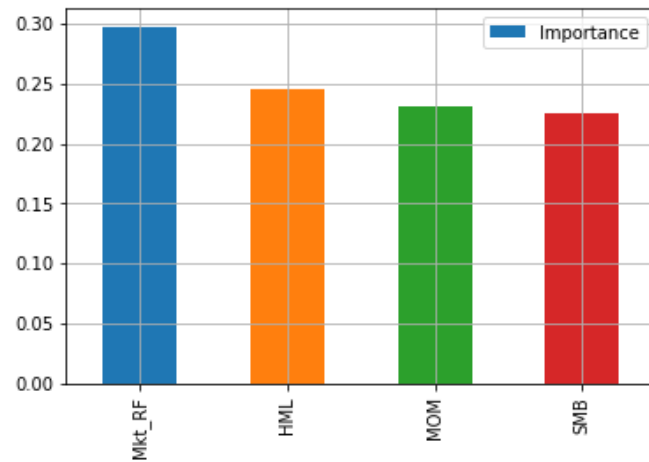


Best parameter (CV score=-0.001):  
 {'pca\_n\_components': 7}  
 RSME Based On Linear Regression: 0.017031892214731736

## Macroeconomic



Best parameter (CV score=0.137):  
 {'GradientBoosting\_learning\_rate': 0.01, 'GradientBoosting\_max\_depth': 4, 'GradientBoosting\_n\_estimators': 100, 'GradientBoosting\_subsample': 0.5, 'pca\_n\_components': 6}  
 RSME Based On Gradient Boosting: 0.015977497904660194



# Summary Results: Best Performing Model

- Evaluated each factor model using classification (accuracy) and regression (RMSE)
- The best model is chosen based on accuracy and RMSE

Models	Classification Accuracy	Regression RMSE
Fama-French-Carhart 4-factor model	77% Logistic Regression	0.0153 Linear Regression
Risk-based factor model	69% Logistic Regression	0.0170 Linear Regression
Macroeconomic factor model	63% Logistic Regression	0.0159 Gradient Boosting

*Fama-French-Carhart has the best predictive power across the 3 models using logistic regression and Linear Regression. Not surprisingly, AQR also uses the same factor model*

# Conclusion and Recommendations

- Given models performance, it is possible to predict (and mirror) GMHF performance using the Fama-French-Carhart, risk-based and macroeconomic factor models
- Among the three factor-models, Fama-French-Carhart best explain Global Macro Hedge Funds' performance
- Among all the features (or factors), market performance, foreign exchange look back straddle and small cap stock performance best predict GMHF returns
- Exploiting these indicators might be key to drive alpha
- The model performance could be improved better by doing data engineer work on the dataset. E.g. Data transformation, coefficient analysis, and outlier detection





The image is a collage featuring US currency. A \$10 bill is prominent in the center, showing the number '10' and the text 'UNITED STATES OF AMERICA'. Other bills include a \$1 bill and a \$5 bill. Several coins are scattered around, including a quarter, a dime, and a penny. Overlaid on the bottom half of the image are several financial data tables, likely from a financial magazine or newspaper, showing various investment performance metrics.

Investment	Value	Change	Yield
GLOBAL ASSET MANAGEMENT			
GAM Sterling Management	0171 493 9990		
Stig & Int Inc	588.20	+ 0.94	1.65
-do- Accum	664.25	+ 1.06	1.65
European Inc	176.74	+ 0.68	1.52
Amalgam Inc	155.10		
N American Inc	393.60		
Fair East Inc	378.72		
-do- Accum	392.51		
UK Divid Inc	204.36		
ROVETT (JOHN) UNIT MGMT LTD			
171 378 7979 Dealing:	0171 407 7888		
Equity Inc #	97.85	+ 0.20	4.56
Small Cos	86.49	+ 0.10	0.62
Irish Growth	65.87	+ 0.32	3.11
American Growth	257.04	+ 2.08	
Japan Growth	69.84	+ 0.59	
Greater China	195.26	+ 1.81	0.16
Strategic	159.51	+ 0.46	
European Growth	115.78	+ 0.90	
Growth	165.26	+ 0.73	
	18.83	+ 0.1022	4.00
	17.7357	+ 0.54	2.15
LAURENCE KEEN UNIT TRUST MGMT			
0171 407 5966			
Bridge Income	292.22	+ 1.45	4.98
Inc & Growth Inc	62.51	+ 0.38	4.17
Smaller Cos	83.93	+ 0.16	1.20
LAURENTIAN UNIT TRUST MGMT LTD			
Enq: 01452 371 500 Dig: 01452 371 623			
Growth Trust	291.60	+ 2.40	1.79
High Income	109.90	+ 0.10	4.45
European Trust	85.52	+ 0.27	0.84
American Trust	110.20	+ 0.70	1.7
MARTIN CURRIE UNIT			
0131 479 4646			
Int Income	79.50		
European	104.40		
Income	80.38		
UK Growth	89.72		
UK Small Cos	179.30		
Asian Opps Fd	64.45		
Global Growth	87.35		
Japan	127.30		
Emerging Mkts	119.50		
Int Growth	60.07		
UK Growth	37.62		
Asian Opps Fd	60.58		
Global Growth			
MATHESON UNIT TRUSTS LTD			
0161 831 7433			
Select Portfolio	100		
MAYFLOWER MANAGEMENT			
0171 407 5966			
Income			
Global Inc			
UK Leaders			
Int Leaders			
PAM My Bal Gwth			
MERCURY FUND LTD			
Dealing: 0800 445			
-do- Accum			

# Frameworks Used

Frameworks	Theoretical	Empirical
Fama-French-Carhart Four Factor Model	Market, size, value and momentum explain stock performance	$(R_i - R_f) = \alpha_i + \beta_{MKT}(R_{MKT} - R_f) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{UMD}(UMD) + e_i$
Trend Following Factors	<p><b>Trend-Following Risk Factors (3):</b></p> <ul style="list-style-type: none"> <li>-Bond Trend-Following Factor</li> <li>-Currency Trend-Following Factor</li> <li>-Commodity Trend-Following Factor</li> </ul> <p><b>Equity-oriented Risk Factors (2):</b></p> <ul style="list-style-type: none"> <li>-Equity Market Factor</li> <li>-The Size Spread Factor</li> </ul> <p><b>Bond-oriented Risk Factors (2):</b></p> <ul style="list-style-type: none"> <li>-The Bond Market Factor</li> <li>-The Credit Spread Factor</li> </ul>	$(R_i - R_f) = \alpha_i + \beta_1(PTFSBD) + \beta_2(PTFSFX) + \beta_3(PTFSCOM) + \beta_4(PTFSIR) + \beta_5(PTFSTK) + \beta_6(DGS10) + \beta_7(CS\_factor) + e_i$
Macroeconomic Factors	Default spread, aggregate dividend yield, the growth rate of real Gross Domestic Product (GDP) per capita, inflation rate, equity market index, term spread, short-term interest rate changes, and unemployment rate	$(R_i - R_f) = \alpha_i + \beta_1(DEF) + \beta_2(DIV) + \beta_3(GDP) + \beta_4(INFLTN) + \beta_5(MKT) + \beta_6(RREL) + \beta_7(TERM) + \beta_7(UNEMP) + e_i$
Volatility	Volatility index	$(R_i - R_f) = \alpha_i + \beta_1(VIX) + e_i$

# Data Preparation

Fama-French-Carhart 4 Factor Model (combination of market risks)

Variables	Description	# of observations	Timeframe	Corrected to	Source
<b>Mkt-RF</b>	Rm-Rf, the excess return on the market	1,111 monthly data points	July 1926 to Jan 2019	Jan 1994 to Dec 2018	Kenneth R. French - Data Library
<b>SMB</b>	Size factor: small stocks relative to large stocks	1,111 monthly data points	July 1926 to Jan 2019	Jan 1994 to Dec 2018	Kenneth R. French - Data Library
<b>HML</b>	Value factor: value stocks relative to growth stocks	1,111 monthly data points	July 1926 to Jan 2019	Jan 1994 to Dec 2018	Kenneth R. French - Data Library
<b>MOM</b>	Tendency for the stock price to continue rising if it is going up and to continue declining if it is going down	1,105 data points Monthly	Jan 1927 to Jan 2019	Jan 1994 to Dec 2018	Kenneth R. French - Data Library

# Data Preparation

Trend-Following factors under Fung and Hsieh (directional / trend risks)

Variables		Description	# of observations	Timeframe	Corrected to	Source
PTFSBD		Return of PTFS Bond lookback straddle	301 data points	Jan 1, 1994 to Jan 1, 2019	Jan 1994 to Dec 2018	David A. Hsieh's Data Library: Hedge Fund Risk Factors
PTFSFX		Return of PTFS Currency Lookback Straddle	301 data points	Jan 1, 1994 to Jan 1, 2019	Jan 1994 to Dec 2018	David A. Hsieh's Data Library:
PTFSCOM		Return of PTFS Commodity Lookback Straddle	301 data points	Jan 1, 1994 to Jan 1, 2019	Jan 1994 to Dec 2018	Hedge Fund Risk Factors
PTFSIR		Return of PTFS Short Term Interest Rate Lookback Straddle	301 data points	Jan 1, 1994 to Jan 1, 2019	Jan 1994 to Dec 2018	David A. Hsieh's Data Library:
PTFSSTK		Return of PTFS Stock Index Lookback Straddle	301 data points	Jan 1, 1994 to Jan 1, 2019	Jan 1994 to Dec 2018	Hedge Fund Risk Factors
The Credit Spread Factor	DBAA	Moody's Baa yield	398 data points 33 years Monthly obs	Jan 1, 1986 to Jan 1, 2019	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis
	DGS10	10-year treasury constant maturity yield	686 data points	Jan 1, 1962 to Feb 1, 2019	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis
The Bond Market Factor	DGS10	The monthly change in the 10-year treasury constant maturity yield	686 data points	Jan 1, 1962 to Feb 1, 2019	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis



# Data Preparation

Macroeconomic variables by Bali, Brown and Caglayan (2014)

Variables	Description	# of observations	Timeframe	Corrected to	Source
DEF	default spread measured as the difference between yields on BAA-rated and AAA-rated corporate bonds	1,202 data points 100 years Monthly obs	Jan 1, 1919 to Feb 1, 2019	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis
DIV	aggregate dividend yield on the Standard&Poor's (S&P)500Index	1,768 data points	Jan 1871 to Dec 2018	Jan 1994 to Dec 2018	Robert Shiller's online data library
GDP	U.S. monthly Growth rate of real GDP per capita	719 data points	Feb 1, 1959 to Dec 1, 2018	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis
INF	INF: monthly inflation rate based on the U.S. consumer price index	865 data points	Jan 1, 1947 to Jan 1, 2019	Jan 1994 to Dec 2018	Robert Shiller's online data library
MKT	MKT: excess return on the value-weighted NYSE/Amex/Nasdaq (CRSP) equity market index	666 monthly data points	July 1963 to Dec 2018	Jan 1994 to Dec 2018	Kenneth R. French - Data Library
RREL	RREL: relative T-bill rate, defined as the difference between the three-month T-bill rate and its 12-month backward moving average	1,022 monthly data points	Jan 1, 1934 to Feb 1, 2019	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis
TERM	TERM: term spread measured as the difference Between yields on ten-year and three-month Treasury securities	446 monthly data points	Jan 1, 1982 to Feb 1, 2019	Jan 1994 to Dec 2018	Federal Reserve Bank of St. Louis
UNEMP	UNEMP: the U.S. monthly unemployment rate defined as the number of unemployed as a Percentage of the labor force	854 monthly data points	Jan 1, 1948 to Feb 1, 2019	Jan 1994 to Dec 2018	US Bureau of Labor and Employment Statistics

# Data Preparation

## Volatility Index (market risks)

Variables	Description	# of observations	Timeframe	Corrected to	Source
<b>VVIX Index</b>	CBOE simple proxy for uncertainty, calculated uncertainty betas for individual stocks using the volatility of their implied option volatilities	344 data points Monthly obs	June 30, 1986 to June 29, 2018	Jan 1994 to Dec 2018	Chicago Board Options Exchange (CBOE®) website

## Global Macro Hedge Fund Index (Dependent Variable Y)

Variables	Description	# of observations	Timeframe	Corrected to	Source
<b>HFRI GMHF Index</b>	Index mean return on Global Macro Hedge Funds in the US	300 data points	Jan 1, 1994 to Dec 1, 2018	Jan 1994 to Dec 2018	Hedge Fund Research Index

# References

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