"Big Data" Meets "Deep Learning"

Rick Davis
BrandLoyalties, Inc.

This presentation will address five questions:

1. What is our "Big Data" and how is it captured?
2. What is the nature of the signals that can be produced?
3. Can those signals produce Alpha in fundamental / discretionary trading strategies?
4. Can those same metrics enhance returns in traditional quantitative / systematic portfolios?
5. Why does ML / AI work so well with "Big Data"?

Question 1.

What is our "Big Data" and How is it captured?

Big Data

/bɪg/ dey-t*uh* ; noun (*slang, found in early 21st century financial/technical jargon*):

1. The vast amounts of information generated – consciously or unconsciously – by billions of people every day as they simply go about their plugged-in and "app" powered life during the 21st century.

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How does this data get captured?

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One way is to scan the web each and every night.

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So, why doesn't everyone do exactly that?

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The Web is Vast & Noisy

- Web “Big Data” is truly big, roughly 30 zettabytes
- Bandwidth and Latency fluctuate day-to-day, hour-to-hour
- Analysis requires sophisticated normalization strategies to allow comparisons over time
- Context and demographic issues require complex multi-variate analysis

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Question 2.

What is the nature of the signals that can be produced?

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Business Intelligence

- Product, merchant or price comparisons
- Consumer forums and crowd sourced reviews
  - Third party review sites
  - Merchant site reviews
- Social media references

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What do consumers mention on line that can be of interest to investors?

Brand Names

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We call each time a consumer refers to a corporate brand name as a "citation" of that brand.

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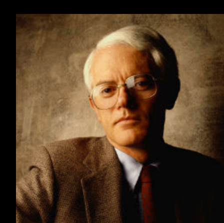
Has anyone ever used consumer brand loyalty as a key investment metric?



Legendary investor Peter Lynch of the Fidelity Magellan Fund utilized what he called "the power of common knowledge" to select candidate equities that warranted his rigorous in-depth fundamental analysis.

He initially utilized de-facto focus groups of family, friends and co-workers to find which brands consumers preferred.

The idea of using "Brand Loyalties" to identify equities for further rigorous fundamental scrutiny was alive by 1977.

And it worked for Peter. From 1977-1990 the average annual return experienced by Magellan's shareholders was over 29%.

"Big Data" offers an opportunity to adapt this approach and bring it into the 21st Century.

"Big Data" research utilizes the world's largest focus group – the Internet – to track the brand names cited by hundreds of millions of consumers every single night.

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How can anyone make sense out of consumer "citations" of Brand Names?

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"Citation" Statistics

- Seasonally Adjusted Citation Rates
- Percentile Rankings of Citation Share Growth
  - Percentiles normalize for coverage growth
  - Share normalizes for bandwidth noise
- Correlation Data
  - Citation share to revenue
  - Causality Chain: Citation > Revenue > Earnings > Price
- Detection of "Event" Spikes (Samsung, UAL, Volkswagen)

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Compliance Friendly

- All "Citations" are publicly available – anyone with a browser can see them.
- All of the data collected is totally anonymous, making the lexicon fully compliant with the GDPR and any other privacy regulations.
- The only material that we store is a cumulative lexicon (vocabulary list) of words being used on the internet on that day.
- Our lexicon is in full compliance with the United States Copyright Act of 1976, 17 U.S.C. § 107. A statistical or lexicographic study of vocabularies found on the web constitutes a "fair use" research of words that are themselves in the public domain.

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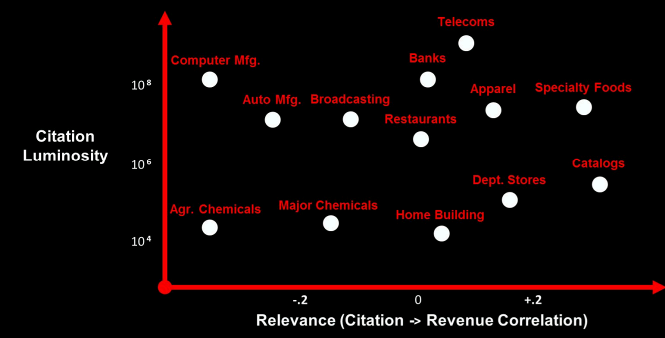
Definitions:

- Luminosity: the amount of “citations” per unit of time.
- Relevance: how tightly the “citation” frequency correlates to revenue.

Luminosity and Relevance by Industry:



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How many equities have sufficient “luminosity” to have a statistically robust signal?

(e.g., >3σ signal-to-noise ratio)

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Roughly 65% of the Russell 3000 have citation signal-to-noise ratios > 3σ.

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Question 3.

Can those signals produce Alpha in fundamental / discretionary trading strategies?

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How do “citation” based metrics correlate with real-world corporate performance?

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Positive Correlations

- ~40% of the Russell 3000 have materially positive citation to revenue correlations
- Some equities have recent citation to revenue correlations exceeding 90%
  - LUV – Southwest Airlines Co.
  - IBRK – Interactive Brokers Group, Inc.
  - FRAN – Francesca’s Holdings Corp.
  - JCP – J.C. Penney Co., Inc.
  - JWN – Nordstrom, Inc.

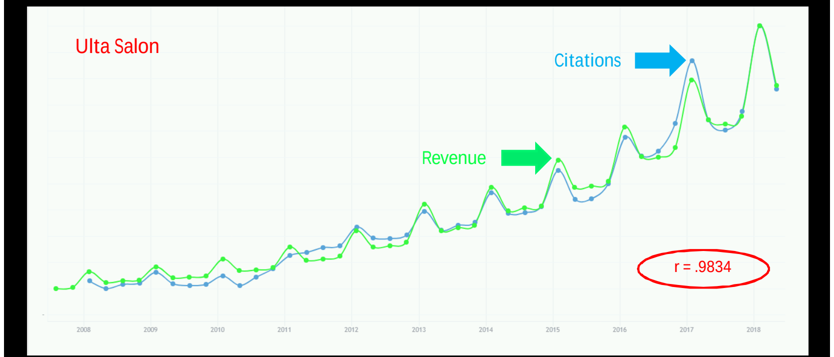

Chart Courtesy of Adaptive Management

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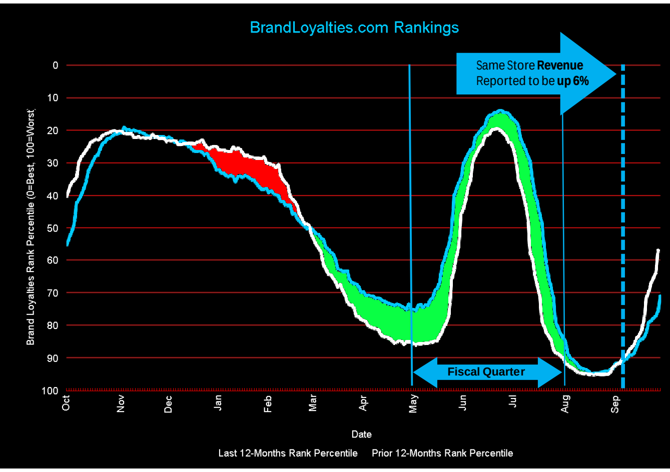
How can a discretionary or fundamental portfolio manager use the data?



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BrandLoyalties.com Alerts For 10/11/2018

Lakewood, Colorado at 10-10-2018 23:34:17

BrandLoyalties Alerts for 10 Calendar Days Ending 10/11/2018

Symbol	Equity	Percentile Ranking (1)	Correlation Percentile (2)	Event Risk (3)	Alert Type	Alert Date
AAN	AARON'S INC.	76.4%	71.3%	20.9%	Recovered OUT of Bottom 20%	10/09/2018
AAPL	APPLE INC.	85.1%	84.4%	0.8%	Strengthened OUT of Bottom 10%	10/05/2018
ABBV	ABBVIE INC.	79.6%	71.1%	10.8%	Recovered OUT of Bottom 20%	10/10/2018
ABCD	CAMBIUM LEARNING GROUP INC.	52.4%	83.9%	16.1%	Recovered OUT of Bottom 20%	10/03/2018
ABCO	THE ADVISORY BOARD COMPANY	78.3%	--	90.6%	Recovered OUT of Bottom 20%; High Event Risk	10/09/2018
ABEV	AMBEV S.A.	75.5%	79.5%	35.2%	Recovered OUT of Bottom 20%	10/09/2018
ABG	ASBURY AUTOMOTIVE GROUP INC	16.0%	8.7%	41.4%	High Rank, Good Correlation	10/01/2018
ACAT	ARCTIC CAT INC.	93.4%	20.0%	97.2%	High Event Risk	10/01/2018
ACCO	ACCO BRANDS CORPORATION	12.0%	14.6%	19.4%	High Rank, Good Correlation	10/01/2018
ACRX	**ACELRX PHARMACEUTICALS INC.**	**80.5 %**	77.1%	17.2%	**Dropped INTO Bottom 20%**	**10/11/2018**
ACST	ACASTI PHARMA INC.	88.9%	--	94.9%	High Event Risk	10/01/2018
ACT	ACTAVIS INC.	9.7%	5.0%	75.8%	Rose INTO Top 10%	10/03/2018
ADT	ADT CORPORATION	90.9%	85.6%	96.4%	High Event Risk	10/01/2018
ADUS	**ADDUS HOMECARE CORPORATION**	**90.7 %**	15.8%	9.2%	**Dropped INTO Bottom 10%**	**10/11/2018**
ADVS	ADVENT SOFTWARE INC.	53.2%	--	97.8%	High Event Risk	10/01/2018
AER	AERCAP HOLDINGS N.V.	60.1%	4.0%	97.3%	High Event Risk	10/01/2018
AF	ASTORIA FINANCIAL CORPORATION	90.5%	28.7%	96.4%	High Event Risk	10/01/2018
AH	ACCRETIVE HEALTH INC.	85.3%	50.1%	37.3%	Dropped INTO Bottom 20%	10/10/2018
AKAO	**ACHAOGEN INC.**	**20.4 %**	31.0%	53.0%	**Dropped OUT of Top 20%**	**10/11/2018**

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Question 4.

Can those same metrics enhance returns in traditional quantitative / systematic portfolios?

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- That same data can be delivered on a daily overnight "push" or "pull" FTP process.

Symbol	Equity	Percentile Ranking(1)	Price Correlation(2)	Optimal Lag Days(3)	IP Scope(4)	YOY Change Percentile (5)	Revenue Correlation Percentile (6)	Event Risk Percentile (7)	Price Correlation Percentile (8)
AAL	AMERICAN AIRLINES GROUP INC.	28.6%	0.69	99	US	63.4%	24.5%	89.0%	19.2%
AAN	AARON'S INC.	12.1%	0.54	130	US	8.5%	25.4%	33.1%	44.8%
AAP	ADVANCE AUTO PARTS, INC.	87.6%	0.74	34	US	74.3%	68.6%	71.0%	10.1%
AAPL	APPLE INC.	37.4%	0.73	249	US	83.0%	18.6%	7.9%	12.5%
AAWW	ATLAS AIR WORLDWIDE HOLDINGS	1.8%	0.69	13	US	13.7%	46.0%	37.6%	19.5%
ABB	ABB LTD	34.6%	0.54	40	US	11.5%	33.8%	93.4%	45.7%
ABBV	ABBVIE INC.	31.8%	0.58	82	US	10.3%	10.5%	51.0%	39.0%
ABCD	CAMBIUM LEARNING GROUP INC.	59.4%	0.57	68	US	27.8%	92.0%	25.1%	40.1%
ABCO	THE ADVISORY BOARD COMPANY	88.9%	--	--	US	41.5%	64.8%	38.2%	0.0%
ABCW	ANCHOR BANCORP WISCONSIN INC.	5.4%	0.16	136	US	34.8%	--	--	90.1%
ABEV	AMBEV S.A.	19.9%	--	--	US	41.5%	94.9%	68.7%	0.0%
ABG	ASBURY AUTOMOTIVE GROUP INC	94.2%	0.79	167	US	96.6%	82.0%	96.5%	5.4%
ABM	ABM INDUSTRIES INCORPORATED	48.9%	0.65	110	US	18.8%	71.5%	77.8%	24.8%
ABT	ABBOTT LABORATORIES	18.6%	0.66	167	US	64.3%	59.8%	9.5%	22.7%
ACAD	ACADIA PHARMACEUTICALS INC.	97.4%	0.72	39	US	91.5%	98.0%	69.6%	13.5%
ACAT	ARCTIC CAT INC.	3.7%	0.66	164	US	70.3%	95.1%	92.4%	23.4%
ACCO	ACCO BRANDS CORPORATION	96.6%	0.03	184	US	88.8%	28.1%	19.0%	97.2%
ACIW	ACI WORLDWIDE INC.	59.5%	0.15	93	US	81.5%	2.6%	56.5%	91.3%
ACN	ACCENTURE PLC.	75.6%	0.73	143	US	73.4%	71.7%	28.2%	11.3%
Symbol	Equity	Percentile Ranking	Price Correlation	Optimal Lag Days	IP Scope	YOY Change	Revenue Correlation	Event Risk	Price Correlation

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- That same data can be delivered on a daily overnight "push" or "pull" FTP process.
- Metrics provided can include:
  - Current Peer Relative Citation Share Growth Rate
  - YOY Changes in Citation Share
  - Citation Share to Trailing Revenue Correlation
  - Citation Share to Equity Price Correlation
  - "Event Risk" Probability

"Big Data" Meets "Deep Learning"

How do rules-based quantitative / systematic research indexes based on "brand loyalties" metrics perform?

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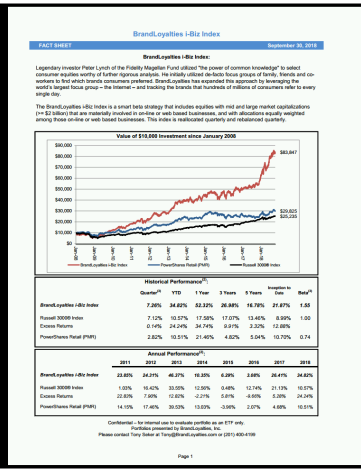
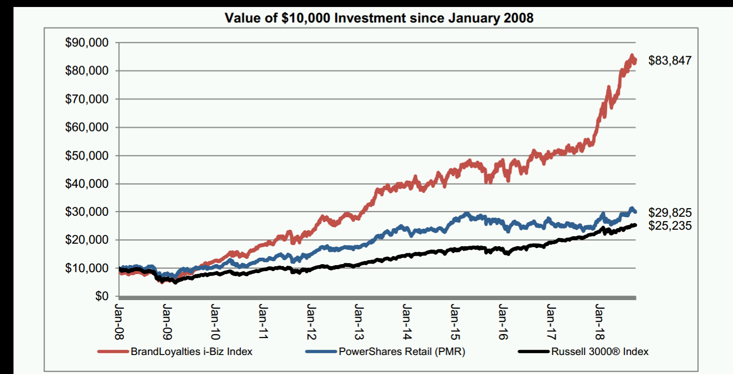
Examples of BrandLoyalties℠ Metrics in 'Smart Beta' Indices (Proforma Performance)

(Proforma Performance Data Covering 01/01/2008 through 09/30/2018)

Index Description	Index Group	3 Months Return Through 09/30/2018	Year to Date Return Through 09/30/2018	12 Months Return Through 09/30/2018	36 Months Annualized Return Through 09/30/2018	60 Months Annualized Return Through 09/30/2018	2008 to Date Annualized Return Through 09/30/2018	2008 to Date Excess Return Through 09/30/2018	Index Value On 10/10/2018	Percentage Change Since 09/30/2018	Index History Download Link	Fact Sheet Download Link
Large Caps Index	Capitalization Tranches	9.33%	13.97%	23.35%	19.64%	16.76%	15.32%	6.34%	43.4475	-6.19%	Index History	Index Fact Sheet
Mid and Large Caps Index	Capitalization Tranches	7.45%	18.68%	27.57%	21.13%	17.21%	16.35%	7.37%	47.7912	-6.29%	Index History	Index Fact Sheet
Consumer Discretionary Index	Broad Consumer Indices	6.21%	17.39%	31.10%	17.91%	15.03%	16.14%	7.15%	47.2905	-5.39%	Index History	Index Fact Sheet
Consumer Staples Index	Broad Consumer Indices	4.24%	12.50%	22.79%	18.09%	15.10%	16.13%	7.14%	47.5498	-4.81%	Index History	Index Fact Sheet
Consumer Goods Index	Broad Consumer Indices	5.42%	16.10%	25.36%	19.31%	15.92%	16.50%	7.52%	48.9228	-5.40%	Index History	Index Fact Sheet
Consumer Services Index	Broad Consumer Indices	8.49%	10.52%	18.12%	14.93%	14.55%	15.94%	6.96%	46.4814	-5.35%	Index History	Index Fact Sheet
Retail Index	Consumer Sector Indices	7.81%	22.76%	37.10%	21.37%	19.83%	17.32%	8.33%	52.4487	-5.90%	Index History	Index Fact Sheet
Apparel Index	Consumer Sector Indices	6.58%	30.70%	50.54%	23.65%	18.18%	18.20%	9.21%	56.0214	-7.28%	Index History	Index Fact Sheet
Food Index	Consumer Sector Indices	5.92%	6.18%	18.28%	15.07%	12.55%	15.00%	6.01%	43.6465	-2.93%	Index History	Index Fact Sheet
Dining Index	Consumer Sector Indices	4.35%	12.56%	26.11%	21.83%	17.95%	17.62%	8.64%	54.2768	-5.32%	Index History	Index Fact Sheet
Hospitality Index	Consumer Sector Indices	8.72%	15.01%	22.79%	15.63%	15.50%	18.37%	9.38%	57.7651	-5.84%	Index History	Index Fact Sheet
Travel Index	Consumer Sector Indices	8.70%	17.34%	29.01%	17.65%	16.85%	18.14%	9.16%	56.2842	-6.37%	Index History	Index Fact Sheet
Technology Index	Consumer Sector Indices	14.40%	31.11%	37.74%	29.90%	21.30%	15.60%	6.61%	43.2845	-8.99%	Index History	Index Fact Sheet
Lifestyle Index	Consumer Sector Indices	5.16%	16.49%	27.23%	17.91%	15.00%	16.34%	7.35%	48.4114	-4.94%	Index History	Index Fact Sheet
Guilty Pleasures Index	Consumer Sector Indices	2.80%	14.07%	25.64%	18.24%	14.15%	16.92%	7.94%	51.1741	-4.70%	Index History	Index Fact Sheet
i-Biz Index	Consumer Sector Indices	7.26%	34.82%	52.32%	26.98%	16.78%	21.86%	12.87%	76.8541	-8.34%	Index History	Index Fact Sheet

Updated Daily on BrandLoyalties Home Page: www.BrandLoyalties.com





Historical Performance[2]:

	Quarter[3]	YTD	1 Year	3 Years	5 Years	Inception to Date	Beta[3]
BrandLoyalties i-Biz Index	***7.26%***	***34.82%***	***52.32%***	***26.98%***	***16.78%***	***21.87%***	***1.55***
Russell 3000® Index	7.12%	10.57%	17.58%	17.07%	13.46%	8.99%	1.00
Excess Returns	*0.14%*	*24.24%*	*34.74%*	*9.91%*	*3.32%*	*12.88%*	
PowerShares Retail (PMR)	2.82%	10.51%	21.46%	4.82%	5.04%	10.70%	0.74

Annual Performance[2]:

	2011	2012	2013	2014	2015	2016	2017	2018
BrandLoyalties i-Biz Index	***23.85%***	***24.31%***	***46.37%***	***10.35%***	***6.29%***	***3.08%***	***26.41%***	***34.82%***
Russell 3000® Index	1.03%	16.42%	33.55%	12.56%	0.48%	12.74%	21.13%	10.57%
Excess Returns	*22.83%*	*7.90%*	*12.82%*	*-2.21%*	*5.81%*	*-9.66%*	*5.28%*	*24.24%*
PowerShares Retail (PMR)	14.15%	17.46%	39.53%	13.03%	-3.96%	2.07%	4.68%	10.51%

“Big Data” Meets “Deep Learning”

How Do the Ranking Quintiles Perform over time?

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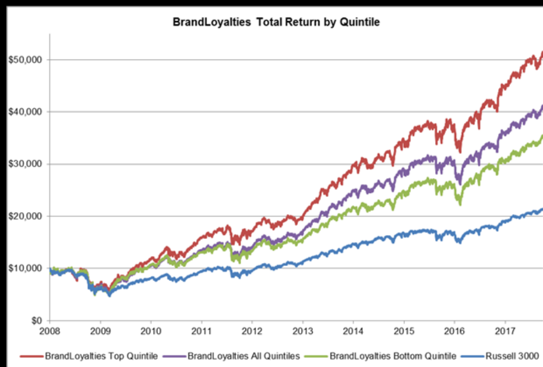

Generating Alpha from “Big Data” Sets

Question 5.

Can “Big Data” metrics work with ML / AI?

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Why does ML / AI work so well with “Big Data”?

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Machine Learning

- “Big Data” is messy, turbulent and unstructured – it is chaotic in every sense of the word.
- Conventional “rules” based logical approaches often fail in chaotic environments.
- Context is critical, and single variate analysis cannot deal with context sensitive data
- Machine Learning is inherently multi-variate and it can learn to deal with rapidly evolving environments

“Big Data” Meets “Deep Learning”

Simply put:

Machine Learning can find relationships and dependencies that human experts cannot see within the chaos of “Big Data.”

“Big Data” Meets “Deep Learning”

Simply put another way:

Humans and “rules” based approaches cannot deal with the chaos in “Big Data.”

“Big Data” Meets “Deep Learning”

Disclaimers

- We are data providers, not portfolio managers
- Our ML / AI experience has been strictly “proof of concept” – not in a production portfolio environment
- We do know that our data is being used in production Machine Learning environments – and suspect that it is being adapted by more and more of our clients

“Big Data” Meets “Deep Learning”

How do we suggest that portfolio managers learn to use ML / AI with our metrics?

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Our Suggestions

- "Newbies" should start with a Python based Neural Network platform (e.g. scikit-learn v0.20) before moving to Google's Tensor Flow
- Model each of our metrics in single factor models and determine relative importance weightings (using Garson's algorithm) for final multifactor models
- Train the model (e.g. sklearn.neural_network.MLPClassifier) on rolling two year periods with the goal of predicting the following 30 day ticker-by-ticker excess return quintiles
- Use the ticker-by-ticker predicted excess returns quintiles to overweight / underweight equities in model portfolio

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How hard is it to get started in Machine Learning?

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Ticker = 'AMZN'

Date	CitSlopePct	YOYCitPct	YOYSharePct	PctlRank	PriceCorrPct	HistExcess	FutExcess	Quintile
7/1/2018	0.019237	0.778083	0.758502	0.9032	0.8864	0.851597	0.895441	5
7/2/2018	0.041566	0.771213	0.755411	0.8870	0.8985	0.889042	0.894755	5
7/3/2018	0.029533	0.776099	0.757898	0.8868	0.9037	0.872253	0.898491	5
7/4/2018	0.017170	0.769574	0.754464	0.8868	0.9037	0.872596	0.886792	5
7/5/2018	0.013045	0.764847	0.748369	0.8680	0.9097	0.846893	0.875043	5
7/6/2018	0.010638	0.764242	0.747083	0.8692	0.9146	0.868222	0.870923	5
7/7/2018	0.007207	0.759780	0.741249	0.8692	0.9146	0.868222	0.870835	5
7/8/2018	0.007207	0.757378	0.739190	0.8692	0.9146	0.868222	0.870835	5
7/9/2018	0.005834	0.751201	0.733699	0.8453	0.9205	0.877145	0.846339	5
7/10/2018	0.005491	0.746054	0.729238	0.8413	0.9241	0.876802	0.852668	5

BrandLoyalties_Demo.py

```python
# Import data via panda
import pandas as pd
ticker = "AMZN"
bl_data = pd.read_csv('.\\Data\\bl_ai_data_' + ticker + '.csv', index_col=0, parse_dates=True)

# Separate Features from Targets
bl_features = bl_data.drop(["YOYCitPct","PctlRank","PriceCorrPct","HistExcess","FutExcess","Quintile"],axis=1)
bl_targets = bl_data.drop(["CitSlopePct","YOYCitPct","YOYSharePct","PctlRank","PriceCorrPct","HistExcess","FutExcess"],axis=1)

# Split data into training and test datasets
from sklearn.model_selection import train_test_split
bl_features_train, bl_features_test = train_test_split(bl_features)
bl_targets_train, bl_targets_test = train_test_split(bl_targets)

# Train using MLPClassifier with Schocastic Gradient Descent ('sgd') solver, using targets in 1d array
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(solver='sgd')
mlp.fit(bl_features_train,bl_targets_train.values.ravel())

# Calculate Preditions
bl_test_predictions = mlp.predict(bl_features_test)
bl_latest_prediction = bl_test_predictions[-1:]

# Print Confusion Matrix
from sklearn.metrics import confusion_matrix
print(confusion_matrix(bl_targets_test.values.ravel(),bl_test_predictions.ravel()))

# Append results to CSV file
results_file = open('.\\results.csv', 'a')
results_file.write('{},{}\n'.format(ticker,bl_latest_prediction))
results_file.close()
```

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		Actual Quintile				
		1	2	3	4	5
Predicted Quintile	1	72	10	2	1	0
	2	13	75	6	2	2
	3	7	11	85	5	2
	4	5	3	5	87	6
	5	3	1	2	5	90

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Ticker	Quintile Prediction
AAN	3
AAPL	5
ABT	4
ACAD	5
AEHR	2
AIZ	2
ALK	5
ALLT	3
AMOV	1
AMSWA	3
AMX	4
AMZN	5
ANET	4
ANFI	1
AOL	1
APEI	2

"Big Data" Meets "Deep Learning"

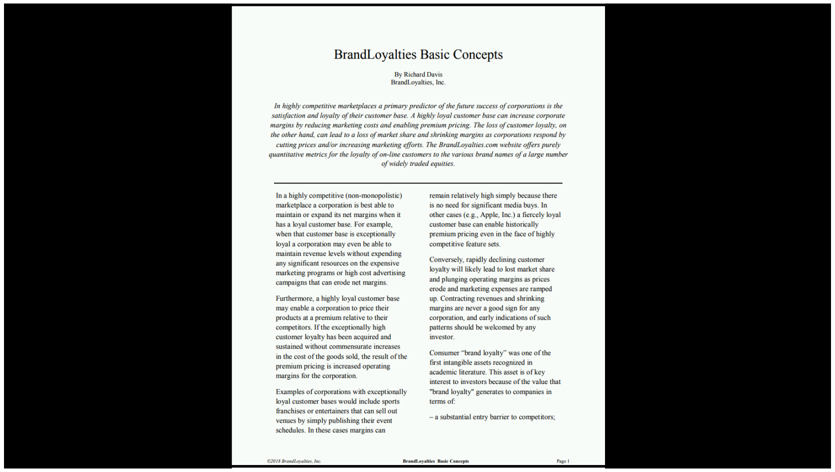
Our Conclusions

- ML / AI (specifically Neural Networks) will work with "Big Data" derived data sets
- Longer training spans significantly improved performance – and those can be accomplished only via proforma data sets
- The Smart Beta "Rule Book" criteria still dominate excess returns:
  - How much to overweight / underweight components
  - What to do with components with no data
- Your mileage will vary
- We provide ML / AI optimized versions of our data upon request

"Big Data" Meets "Deep Learning"

We Can Provide:

- CSV formatted data sets for easy pandas import
- Columns scaled, normalized and optimally signed
  - Key metrics provided as percentiles or slopes
- Training target columns included with feature data



BrandLoyalties Basic Concepts

By Richard Davis
BrandLoyalties, Inc.

In highly competitive marketplaces a primary predictor of the future success of corporations is the satisfaction and loyalty of their customer base. A highly loyal customer base can increase corporate margins by reducing marketing costs and enabling premium pricing. The loss of customer loyalty, on the other hand, can lead to a loss of market share and shrinking margins as corporations respond by cutting prices and/or increasing marketing efforts. The BrandLoyalties.com website offers purely quantitative metrics for the loyalty of on-line customers to the various brand names of a large number of widely traded equities.

In a highly competitive (non-monopolistic) marketplace a corporation is best able to maintain or expand its net margins when it has a loyal customer base. For example, when that customer base is exceptionally loyal a corporation may even be able to maintain revenue levels without expending any significant resources on the expensive marketing programs or high cost advertising campaigns that can erode net margins.

Furthermore, a highly loyal customer base may enable a corporation to price their products at a premium relative to their competitors. If the exceptionally high customer loyalty has been acquired and sustained without commensurate increases in the cost of the goods sold, the result of the premium pricing is increased operating margins for the corporation.

Examples of corporations with exceptionally loyal customer bases would include sports franchises or entertainers that can sell out venues by simply publishing their event schedules. In these cases margins can remain relatively high simply because there is no need for significant media buys. In other cases (e.g., Apple, Inc.) a fiercely loyal customer base can enable historically premium pricing even in the face of highly competitive feature sets.

Conversely, rapidly declining customer loyalty will likely lead to lost market share and plunging operating margins as prices erode and marketing expenses are ramped up. Contracting revenues and shrinking margins are never a good sign for any corporation, and early indications of such patterns should be welcomed by any investor.

Consumer "brand loyalty" was one of the first intangible assets recognized in academic literature. This asset is of key interest to investors because of the value that "brand loyalty" generates to companies in terms of:

– a substantial entry barrier to competitors;

"Big Data" Meets "Smart Beta"

Richard C. Davis

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Currently "big data" is a very trendy topic within the investment community. It is also somewhat elastically defined. One variation of big data refers to the vast amounts of online data generated by billions of ordinary people (consciously or unconsciously) as they simply go about their web powered, social media addicted, and smart-phone enabled lives. Every online action leaves at least some digital traces behind. Many of those digital "crumbs" are harvested by the usual suspects: the NSA (and its international counterparts), law enforcement agencies, web advertisers, and sundry hackers.

But the investment community is also becoming aware of the business intelligence imbedded in this form of big data[1]—and is ramping up big data spending accordingly.[2] The increased spending is predicated on evidence that big data imbedded intelligence gives active portfolio managers essentially real-time status reports on the intimate relationship between consumer-oriented corporations and their customers. Active portfolio managers have been using big data derived metrics for both tactical and quantitative purposes for some time.[3] Now that same intelligence is being vetted for use in another elastically defined arena: passively managed "smart beta" portfolios. The preliminary results discussed below indicate that passive portfolios with a high tolerance for tracking errors can benefit significantly by utilizing big data metrics in several ways, including alternative weighting methodologies and the selection of unorthodox consumer equities as index components.

"BIG DATA" PRIMER

Before we explore the ways to extract and exploit the business intelligence imbedded in big data, it would be useful to understand the raw source materials that expose information about the relationship between consumer-oriented companies and their customers. Big data is packed with material from consumer activities. That material includes:

- Product searches, price comparisons, coupon huntings;
- Merchant location and/or business hours queries;
- Product or merchant reviews and recommendations (e.g., Yelp);
- Auction entries, online listing services;
- Help, travel, hobby, DIY, and investment forums;
- Social media posting and sharing sites, "tweets"; and,
- Mobile Apps (e.g., "Siri: Where is the nearest Starbucks?").

Web Luminosity Data Applications for Alpha Generation

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Abstract

This paper investigates investment applications of Web Luminosity, a measure of the ubiquity of a company's brands in relevant internet citations. Web Luminosity is important in this research because of its relevance to brand loyalty. Long considered an intangible, brand loyalty is now routinely factored into investment analysts' calculations of the intrinsic value of relevant firms. To do so, many models use brand loyalty proxy metrics interpolated from financial statements. With today's technologies those data are processed instantly and distributed widely, so that much of the competitive edge previously documented in studies is currently difficult to translate into alpha. The other traditional brand loyalty data source is focus groups; they are time-consuming, costly, and may contain sampling bias. Web Luminosity, derived from a corporation's total relevant brand citations on the internet, makes use of a free global focus group proxy, the internet. To do this, extensive mapping and lexicography files are needed to extract only pertinent data. Transforming web luminosity data for a company into an investment signal requires several more analytic steps and a comprehensive framework to determine the signal's relevance and efficacy. This white paper documents that process, then proceeds to the testing phase. First, investment signals are tested to demonstrate their effectiveness in differentiating groups of positive future performers from negative future performers, thus identifying efficacy in long-short portfolios. Then, a core long-only US Large Cap portfolio application is illustrated.

Why is Brand Loyalty Important to Investors?

Brand loyalty is one of the first intangible assets recognized in academic literature. The academic interest derives from the value that brand loyalty generates to companies in terms of:

- A substantial entry barrier to competitors,
- An increase in the firm's ability to respond to competitive threats,
- Greater sales and revenue, and
- A customer base less sensitive to the marketing efforts of competitors.

A practical example of brand loyalty being helpful in providing superior investment returns comes from Peter Lynch of Fidelity Magellan fame. Peter Lynch advocated "liking a store, a product, or a restaurant is a good reason to get interested in a company and put it on your research list"[1] for selecting equities with enough brand loyalty to warrant further fundamental analysis. Peter Lynch also credits brand loyalty as a significant intangible when he argued that

[1] Lynch, Peter. *One Up on Wall Street.* New York: Simon & Schuster, 1989. ISBN 0-7432-0040-3. pp. 16.

"Big Data"

Meets

"Deep Learning"

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