Lucena Research
Predictive Analytics

The Essential Guide to Machine Learning For Traders

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Why Machine Learning for Trading?

The demand for investment strategies formed from unique data with a Quantitative overlay is growing.

Machine Learning is transforming rapidly and with predictive data, AI Classification can achieve or even exceed classification accuracy of humans.

Traditional wealth management has the opportunity to reinvent itself with sophisticated offerings powered by advanced AI technology.

By utilizing ML and predictive analytics, fund managers are finding new ways to support their clients investment objectives, distinguish themselves from the crowd, and justify their fees.

At Lucena we turn knowledge into actionable insights. Our goal for this guide is to help you do the same.

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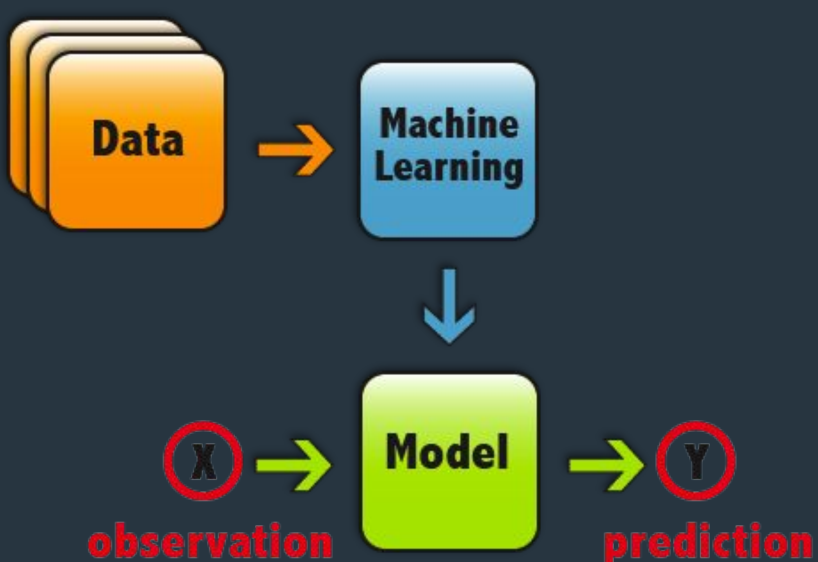
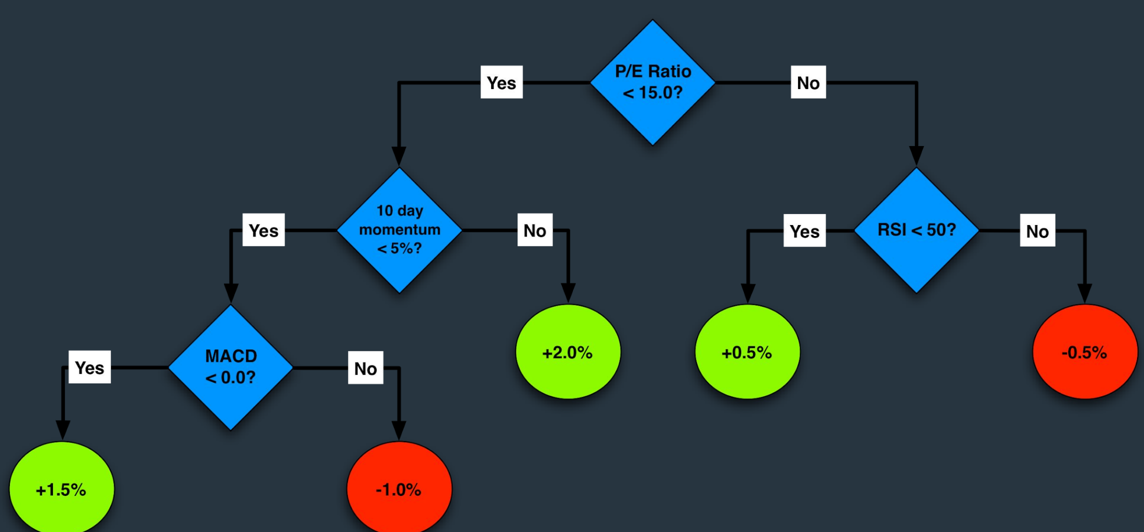
How To Build A Predictive Model

- Start with examples: Factor values & outcomes
- Build a model from examples
- Use model to predict outcomes
- Factor X through model predicts Y
- Many methods can be used. In this guide we will be discussing regression, and classification with traditional ML such kNN and Decision Trees.
- We will then move to more sophisticated methods in deep learning, such as CNN, RNNs and more.



How to Build A Decision Tree

- A decision tree is a flow chart of yes/no questions.
- The end prediction can be used for classification or regression.
- To train your model
  - Find the most predictive factor
  - Split the data based on that factor
  - Repeat
  - For a more robust model, train multiple trees to make a random forest.



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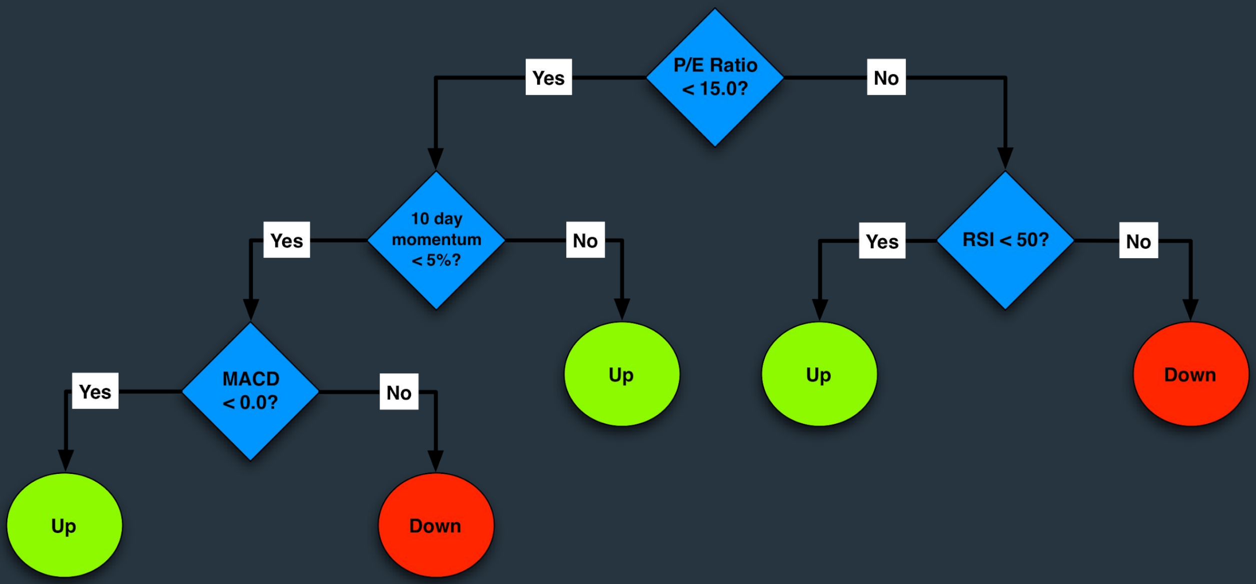
Using Decision Trees For Stocks

Designate your stocks and create a decision tree using yes/no questions. Asses stocks that end on a yes/no up/down basis.

Continue to revise and test your portfolio.



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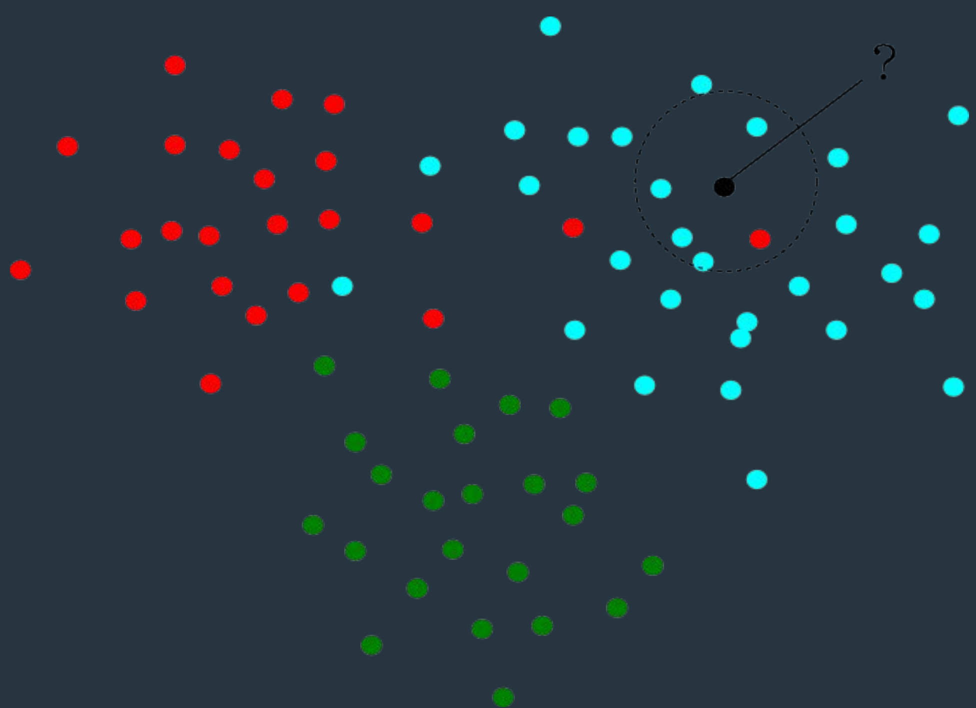
K Nearest Neighbor

kNN solves the same queries as decision trees and can be used for classification and regression.

A query finds the nearest points around a question and gathers majority data to form prediction.

In the example image below, the black mystery dot is surrounded by blue. The kNN model gathers nearest data to classify the missing element as blue.



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Decision Tree Vs kNN

Decision Trees

- Used for classification or regression
- Training is slow, the model has to be given factors, questions and responses
- Doesn't require data normalization

kNN

- Used for classification or regression
- No training, but process can be tedious for a large data pool as the model has to look up every data point
- Requires data normalization

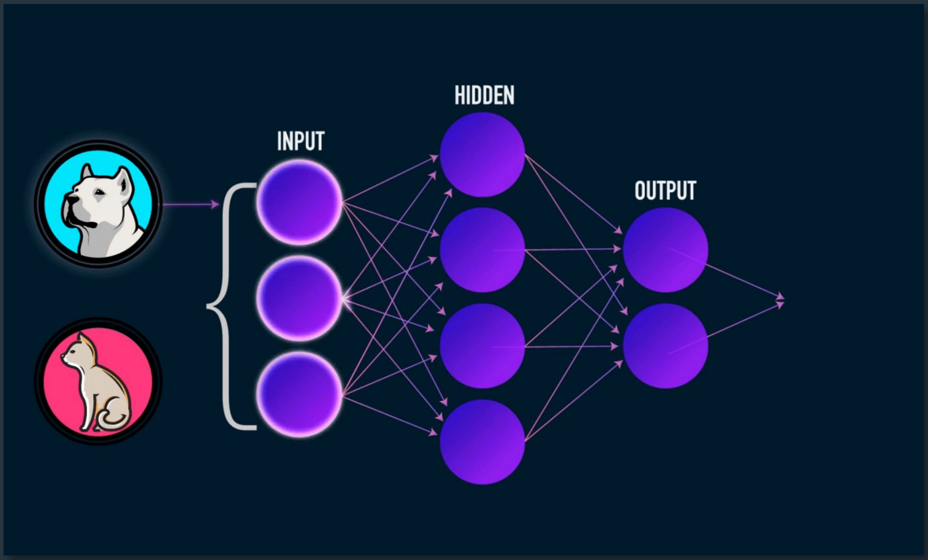
It's important to note that while kNN and Decision Trees are two traditional regression models, they are not able to address certain scenarios for trading.

To form the best strategies for trading, Reinforcement and Deep Learning should be utilized.

The Mechanics of Deep Learning

What is a Deep Neural Network?

- DNNs are able to classify complex relationships between characteristics of an image and its corresponding classification.
- The network consists of layers of neurons (input and hidden) that feed forward information to form an output layer.
- The ML process of classifying an image as a Dog or Cat can also be applied to classify a stock's impending price action.



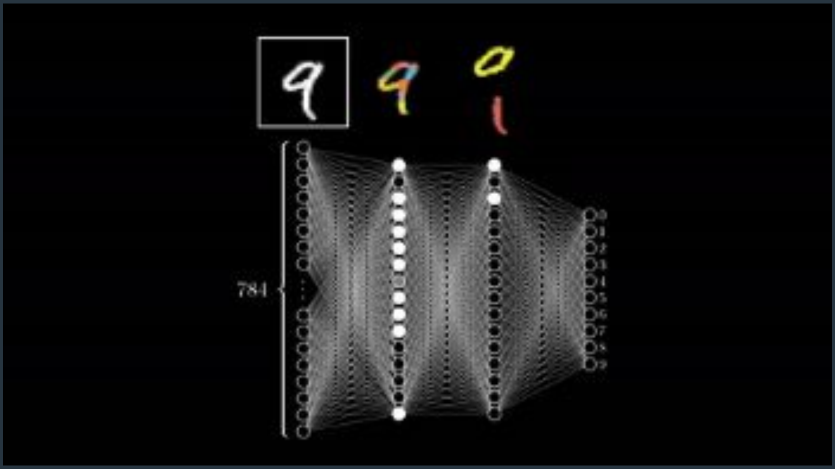
By James Loy. Source: https://towardsdatascience.com/how-to-build-your-own-neural-network-from-scratch-in-python-68998a08e4f6

How A Deep Network Classifies

To understand how deep learning networks learn, let's take a closer look at handwriting recognition.

If you take a simple written digit and ask the network to classify, a fully connected network may look something like the below.

- One layer identifies edges
- Subsequent layers identify patterns
- Output layer identifies the full object



By 3Blue1Brown. Source: https://www.youtube.com/watch?v=aircAruvnKk

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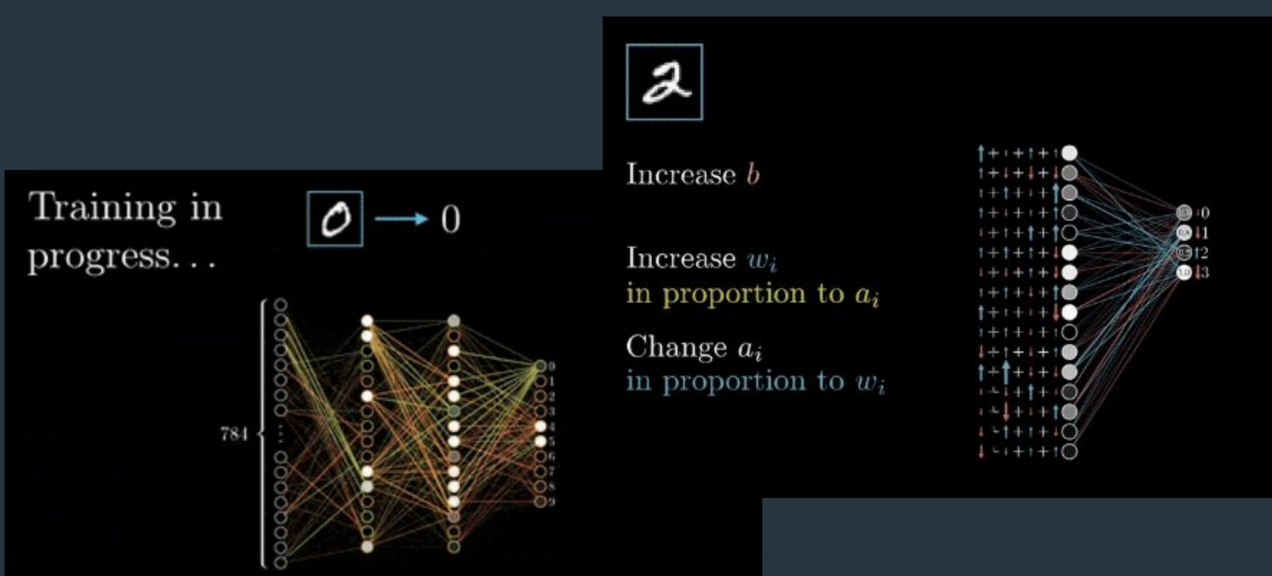
How A Deep Network Learns

A fully connected deep learning network feeds forward by passing votes from one layer to another.

Upon final classification we can assess how far the votes were from a ground truth (perfect knowledge).

A process called Backpropagation feeds backwards and adjusts the weights one layer at a time so that the network gets closer to the desired outcome.

- Image two shows how Backpropagation is manifested by adjusting each layer in turn and dialing the weights of the neurons up or down accordingly.



Images by 3Blue1Brown. Source: https://www.youtube.com/watch?v=aircAruvnKk

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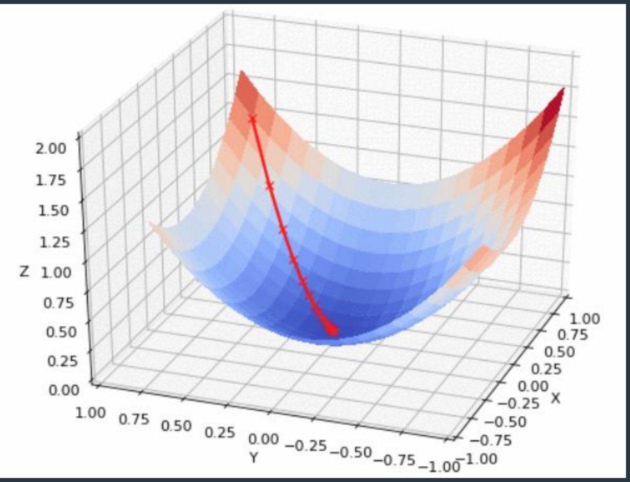
How The Network Makes Adjustments

The network further measures errors through Gradient Descent, the process of searching for the lowest point in a graph that represents the local minimum of the cost function.

The distance between the model's vote and the desired vote is expressed through a simple cost function or Error function.

- The weights of the neurons can algorithmically be changed to "travel" forward or back to get closer to a local minimum of the cost function.
- The pace and direction to adjust the weights of each neuron in order get closer to the desired vote.
- Attempts to reach a local minima based on the slope of the cost function.



The above animation illustrates the Gradient Descent method' Image by Mubaris NK. Source: https://mubaris.com/2017/09/28/linear-regression-from-scratch/

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Neural Networks: Convolutional

Now let's dig deeper into fully connected layers.

A Convolutional Network is an extension of a traditional fully connected deep neural network.

Convolution is derived from the verb To Convolve - a process of combining, merging or transforming information.

CNNs add additional layers to simplify a large complex image being fed through a network.

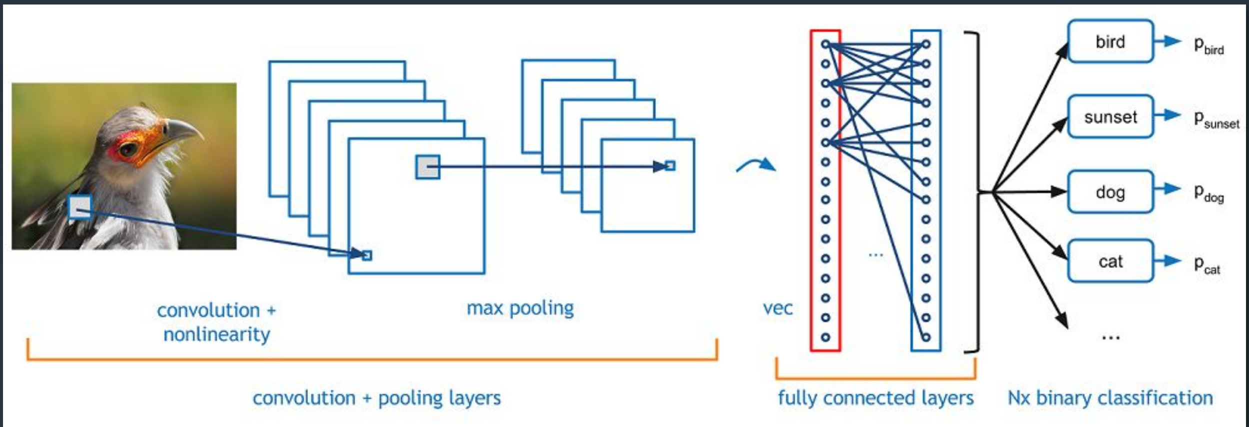
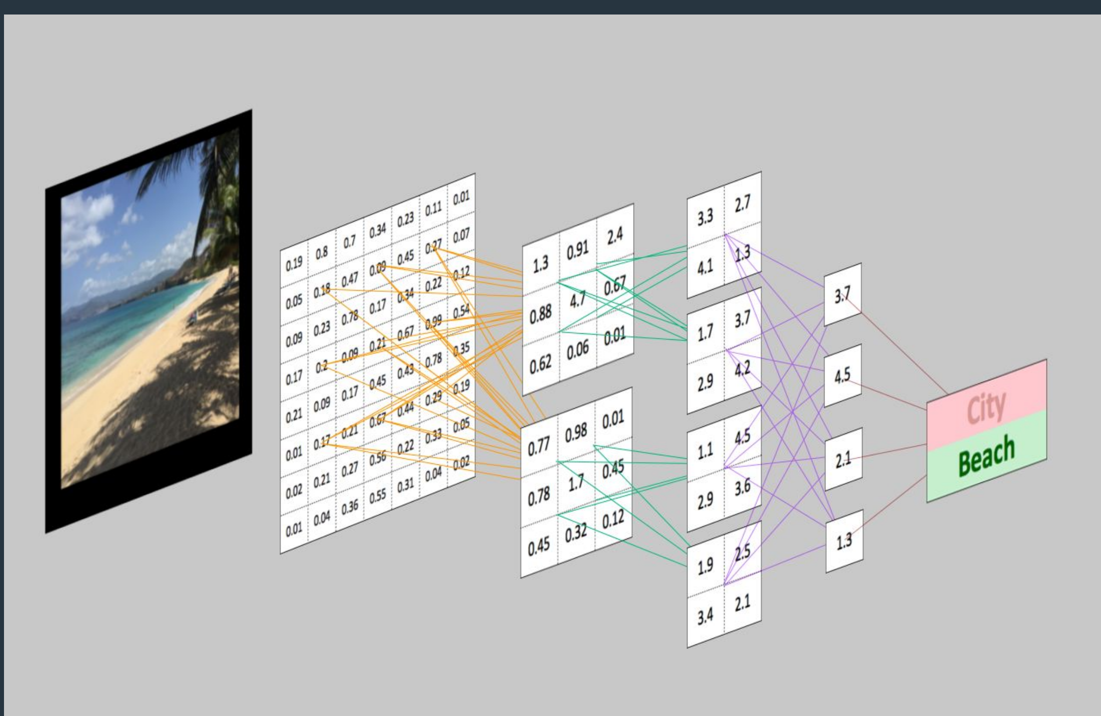


Image by Rob Hess. Source: https://code.flickr.net/2014/10/20/introducing-flickr-park-or-bird/
'CNNs and computer vision' Image by Adam Gibson, Josh Patterson. Source: https://www.safaribooksonline.com/library/view/deep-learning/9781491924570/ch04.html

Neural Networks: Convolutional

CNNs create numerical representations of an image. The networks learn how to create filters that extract receptive fields, or spatial (patterns) from the original image.

The image is convolved in order to extract basic distinguishable characteristics. Filters scan the image and extract features that are most distinguishable about the content of the image.



CNNs and computer vision' Image by Adam Gibson, Josh Patterson. Source: https://www.safaribooksonline.com/library/view/deep-learning/9781491924570/ch04.html

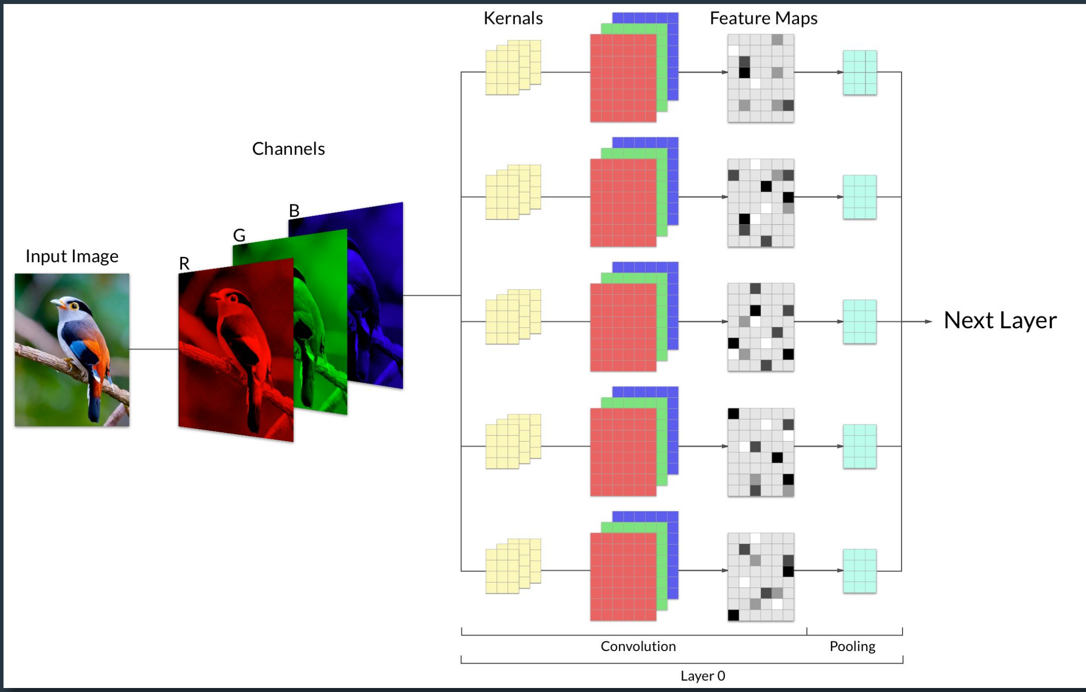
Multichannel Breakdown of an Image

Channels are CNN components designed to support the volume of an image.

The idea is to break down an image into multiple vertical layers stacked above each other.

The complex multi-dimensional image is ultimately merged (or flattened) before being fed into the fully connected layer.

Below you can see three channels (Red Green and Blue) designed to represent the color composition of the image.



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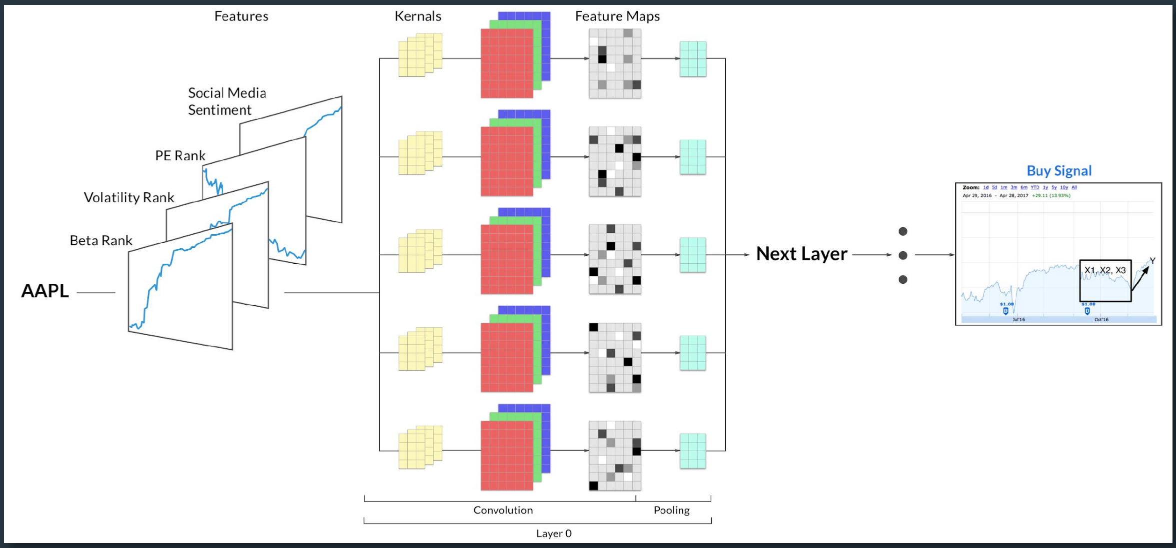
How Do We Apply to Stocks?

Below, time series images of feature values are shown. Each represents a time series value of a data factor that describes the pattern of how the values of the signal transformed over time.

- Each indicator is represented as an image of a time series trend
- Each image can be treated as a channel of more complex images
- The state of a stock is represented as multiple stacked features that forms a complete picture.
- Image can then be classified as whether the underlying stock is about to move higher or lower.



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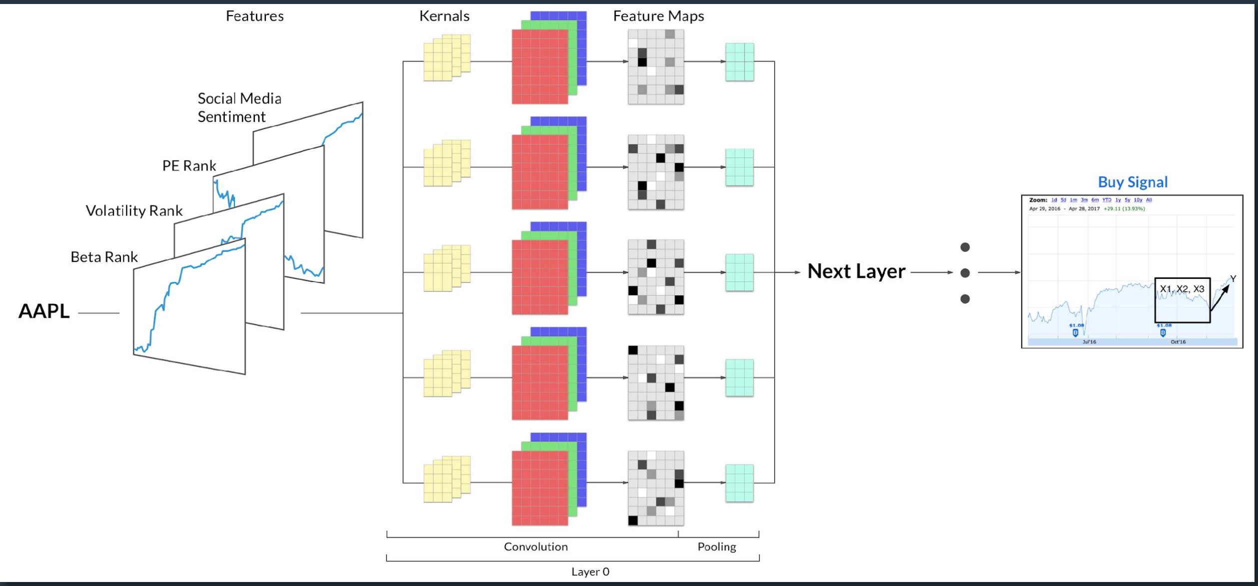
How Do We Apply to Stocks?

We then feed the network with lots of examples of stacked images and the stock's outcome. The machine starts to learn what images are more predictive to a desired future price action over time.



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Sine Wave Validation

Through our research, we have attempted to pass time series values into a fully connected network layer but were unsuccessful in finding predictive value.

We then looked for a richer image representation of the data and came across an interesting approach of converting the sequence of data into a richer image through a method called Recurrent Point or RP.

Below you can see a sine wave time series of 63 data points converted into a 63*63 rich image that represents the Euclidean difference between every two points in the time series. The shades of the cells are proportional to the distance between every two points.

	Strategy Overall	Bench Overall	Strategy TTM	Bench TTM
Abs. Return	231.35%	108.17%	10.22%	16.93%
Rel. Return	123.18%	N/A	-6.71%	N/A
Beta	0.00	N/A	0.00	N/A
Std. Dev	0.03%	1.30%	0.03%	0.69%
Sharpe	28.83	0.47	23.24	1.48
Draw Down	-0.22%	-55.25%	-0.12%	-7.28%
IR	0.13	N/A	-0.59	N/A
R^2	0.00	N/A	0.00	N/A

Historical Summary

	1 Yr	2 Yr	3 Yr	5 Yr	10 Yr
Ann. Return	10.22%	11.48%	13.59%	12.88%	N/A
Std. Dev	0.03%	0.03%	0.03%	0.03%	N/A
Ann. Volatility	0.42%	0.45%	0.42%	0.43%	N/A

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Sine Wave Validation Continued

We chose a sine wave to see if a deep learning model can learn an obvious repetitive pattern.

By applying a simple Logistic Regression (a much simpler form of machine learning model) VOILA –the machine was able to achieve an out-of-sample accuracy of 97.6%.

Under the sine wave is a backtest of a fictitious stock that behaves like a sine wave. Our platform was able to identify and exploit the information in a sine wave after it was converted into a rich image.

Therefore, we have validated that if there is information in the data, we will most likely be able to extract it.

	Strategy Overall	Bench Overall	Strategy TTM	Bench TTM
Abs. Return	231.35%	108.17%	10.22%	16.93%
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Sharpe	28.83	0.47	23.24	1.48
Draw Down	-0.22%	-55.25%	-0.12%	-7.28%
IR	0.13	N/A	-0.59	N/A
R^2	0.00	N/A	0.00	N/A

Historical Summary

	1 Yr	2 Yr	3 Yr	5 Yr	10 Yr
Ann. Return	10.22%	11.48%	13.59%	12.88%	N/A
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Ann. Volatility	0.42%	0.45%	0.42%	0.43%	N/A

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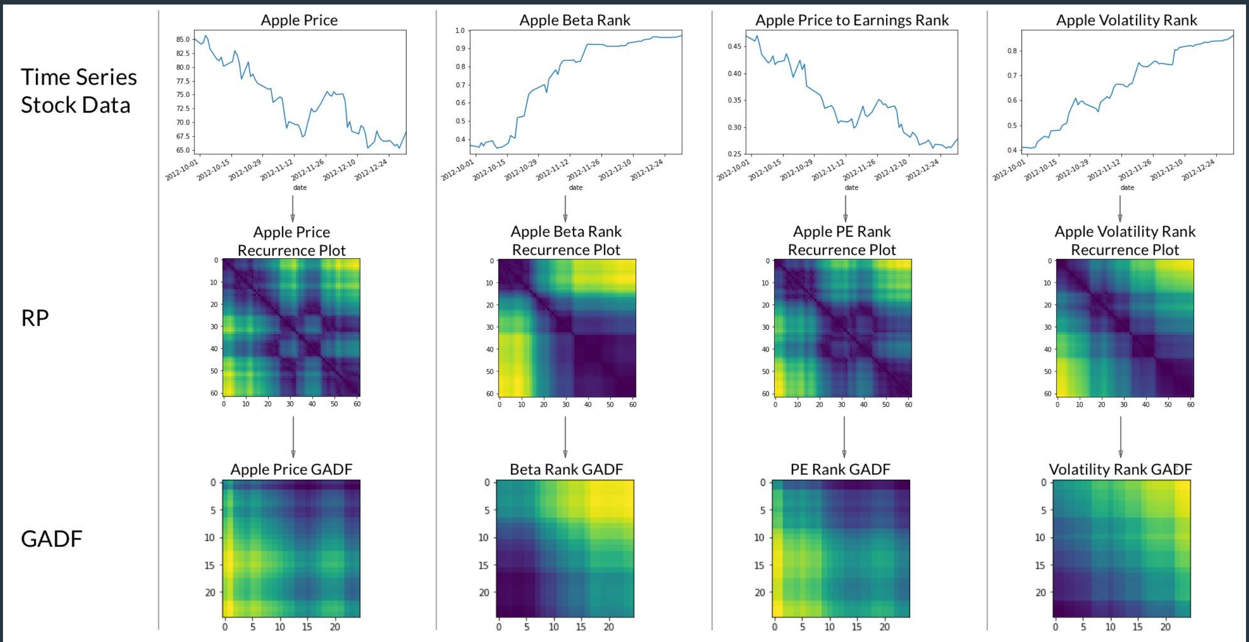
Multichannel with Stock Features

Other time series sequences (trends) can just as easily be migrated to images. Below are a few factors represented as 63 day time series history and then converted into a richer 63*63 rich images.

As you can see - RP is symmetrical across the diagonal of the square. (we lose information efficiency of 50% within the full space coverage)

GADF – Stands for Gramian Angular Difference Field, enables a richer implementation by measuring the distance and the angular difference between time series points and takes advantage of the entire 63*63 space.



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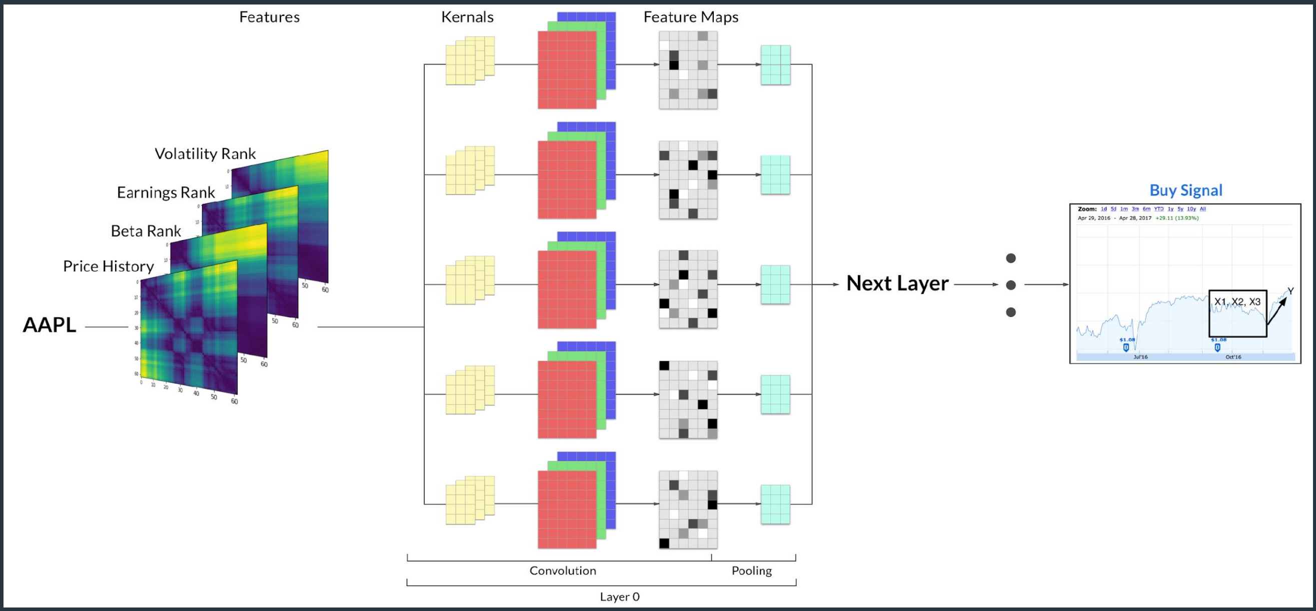
Multichannel Breakdown for Stocks

Can we visually represent the state of a publicly traded company or a stock that would lead to high probability expectancy of its impending price move?

By converting our time series data to richer images and stacking them as channels of a complex image, we now have a comparable model to the traditional multi-color image classification.



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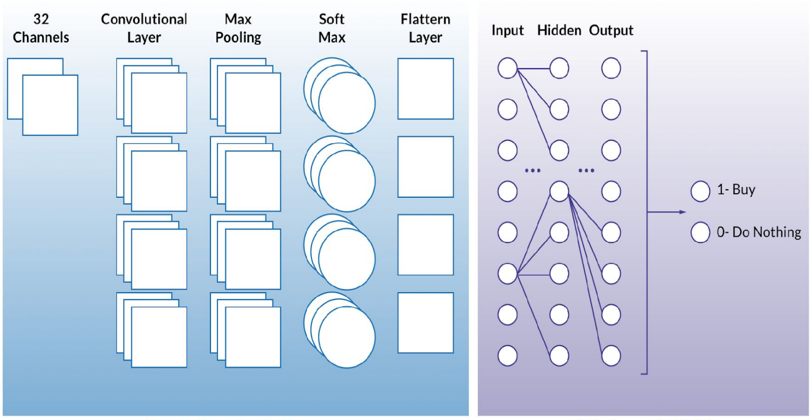
Multichannel Breakdown for Stocks

Here is an example of Lucena's model makeup after testing thousands of permutations through a hyperparameter search.

This model can be used to gather:

- Technical and fundamental features
- Macro Econ Features
- Alternative Data Features including social media and news feed sentiment, and much more!



Convolution + Pooling Layers

Fully Connected ANN

Convolution + Pooling Layers				
Channels	64	32	16	8
Kernel Size	3x3	4x4	5x5	
Stride	1	2	3	
Pooling	2x2	3x3		
Max Pooling	Fixed			
Cross Entropy	Fixed			
Soft Max	Fixed			

Fully Connected ANN				
Fully Connected Layers	Structure 1			
	100	100	30	2
	Structure 2			
	30	30	30	2
Activation Function	1. Relu		2. Sigmoid	

To summarize, we broker our training period in three:

- Hyperparameter searches to find the best model framework
- Training period of the model based on Historical Data
- Validation of the training to produce predictive results to form Buy/Sell recommendation

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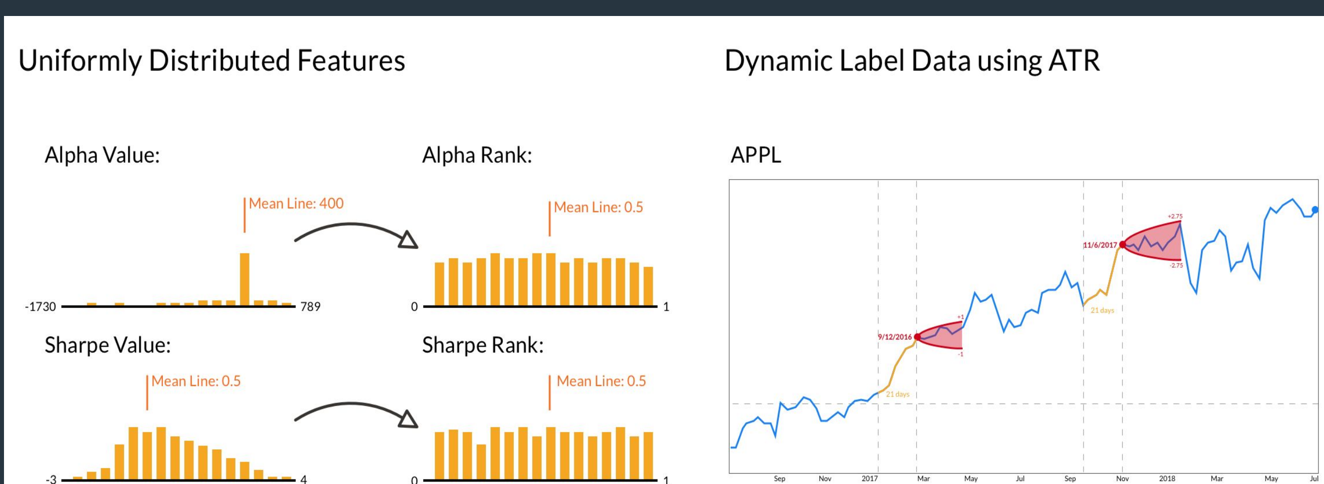
Making Machine Learning Easy

In order to make the selection dynamic to survive the test of time, we will refrain from using hard values.
For example, we label the data dynamically by how a stock ranks relative to its peers vs. absolute value at a particular time (which may be market regime dependent).

The Objective Target of what constitutes a Buy or Sell classification is also dynamic. The buy / or sell are not dependent on an absolute price target (at least 2% higher) but determined based on ATR (Average True Range) which measures a stock's recent volatility.

This way the target price can be changed dynamically based on volatility of the market or the specific stock being evaluated.



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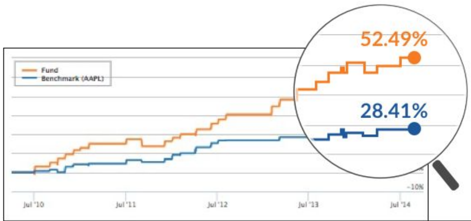
APPL Backtest

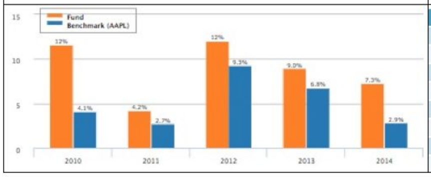
Finally – we wanted to showcase a backtest of APPL (in and out of sample)

Price target is based on on AAPL's 21 day ATR
We buy and hold for 21 days – or until AAPL reaches either the upper or lower ATR threshold.

There are no transaction costs applied. We use Exposure Adjusted Benchmark to measure the strength of the buy signal discounting staying in cash).

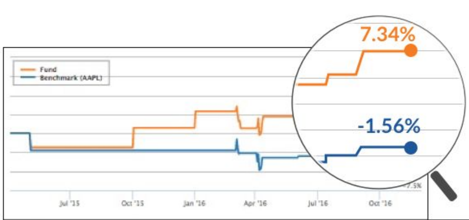
Results are Exposure Adjusted
In Sample: 4/6/2010 to 9/30/2014

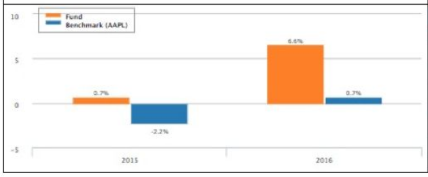




	Strategy Overall	Bench Overall
Abs. Return	52.49%	28.41%
Rel. Return	24.08%	N/A
Beta	0.04	N/A
Std. Dev	0.34%	0.24%
Sharpe	1.76	1.50
Draw Down	-4.38%	-2.22%
IR	-0.72	N/A
R^2	0.04	N/A

Results are Exposure Adjusted
Out of Sample: 4/6/2015 to 12/1/2016





	Strategy Overall	Bench Overall
Abs. Return	7.34%	-1.56%
Rel. Return	8.90%	N/A
Beta	0.02	N/A
Std. Dev	0.27%	0.22%
Sharpe	1.01	-0.26
Draw Down	-3.64%	-4.84%
IR	0.30	N/A
R^2	0.01	N/A

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Why Reinforcement Learning for Trading?

Reinforcement Learning (RL) is derived from historic research in Psychology and can solve more robust problems than Decision Trees and kNN.

RL learning is the process of mapping situations to actions in order to maximize a certain reward or minimize a certain punishment. Similar to a mouse learning to find the right path in a maze, the learner is not told which action to take, but instead must discover which actions yield the highest reward through trial and error.

A predictive signal can be passed into an RL to determine how to best benefit from such signal. With advancements in hardware and ML disciplines, Deep Learning continues to push boundaries and will ultimately provide cognitive reasoning that can match or exceed that of humans.

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Reinforcement Learning

The evolution of RL is very exciting as it perfectly aligns with investment objectives.

- Best suited model for trading; the learner can be trained to optimize the same objective as investors (Ex: risk adjusted return).
- Can solve problems without pre-designated answers.
- Finds a policy rather than classifying and regressing.
- Provides entire strategy including entry and exit conditions based on probability of success.
- The learner tries to distinguish between different states and appropriately consider a policy for:
  - Risk of loss
  - Possible, but unlikely, large return
  - Probable small return
  - Or an inconclusive state by which doing nothing (staying in cash) is smart

To Summarize

It’s no secret that the demand and capabilities of AI and Machine Learning are rapidly growing in the Financial industry. Your clients are looking to entrust their funds with managers who stand out and can validate their fees.

Incorporating Machine Learning and predictive analytics will give you a competitive edge and keep you ahead of the curve.

Lucena’s mission is to provide professionals with the tools needed to rise above the competition through the development and execution of winning investment strategies. Our ML platform aggregates signals from leading data providers and enables investment professionals to find and exploit market opportunities by scientifically validating strategies before risking capital.

Want to test out your strategies in our platform QuantDesk®?

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About Lucena

Lucena Research is an AI technology company founded by renowned Machine Learning expert Tucker Balch, Ph.D, and technology entrepreneur Erez Katz.

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