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Canadian Pension Risk Strategies

Machine Learning in Quant Finance

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MACHINE LEARNING IN QUANT FINANCE

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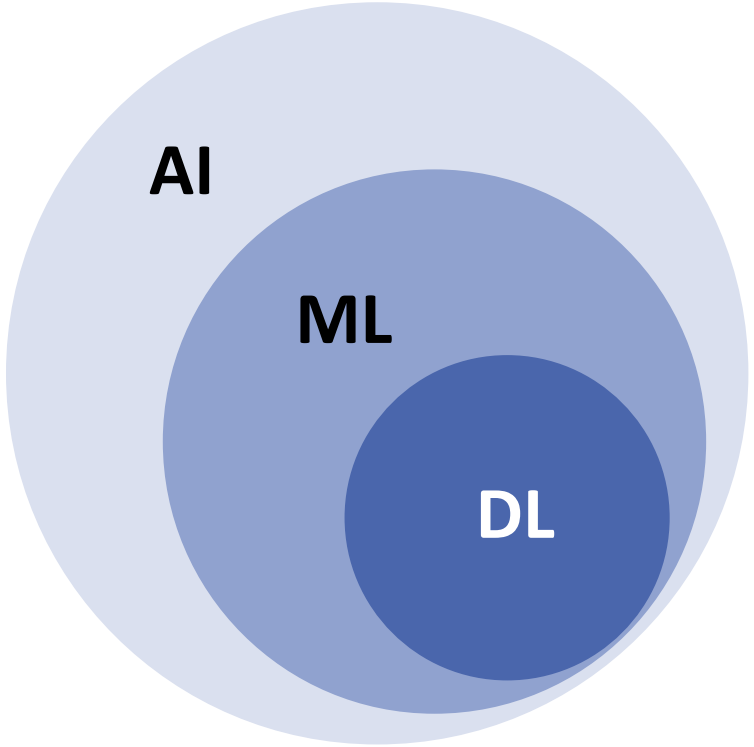
Canadian Pension Risk Strategies

- Definitions, History
- Random Forests
- Neural Networks
- Comparisons; What We've Learned So Far
- A Real Life Example
- Summary

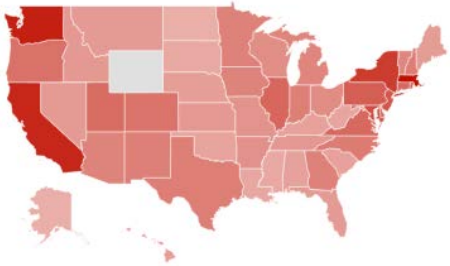
Definitions, History

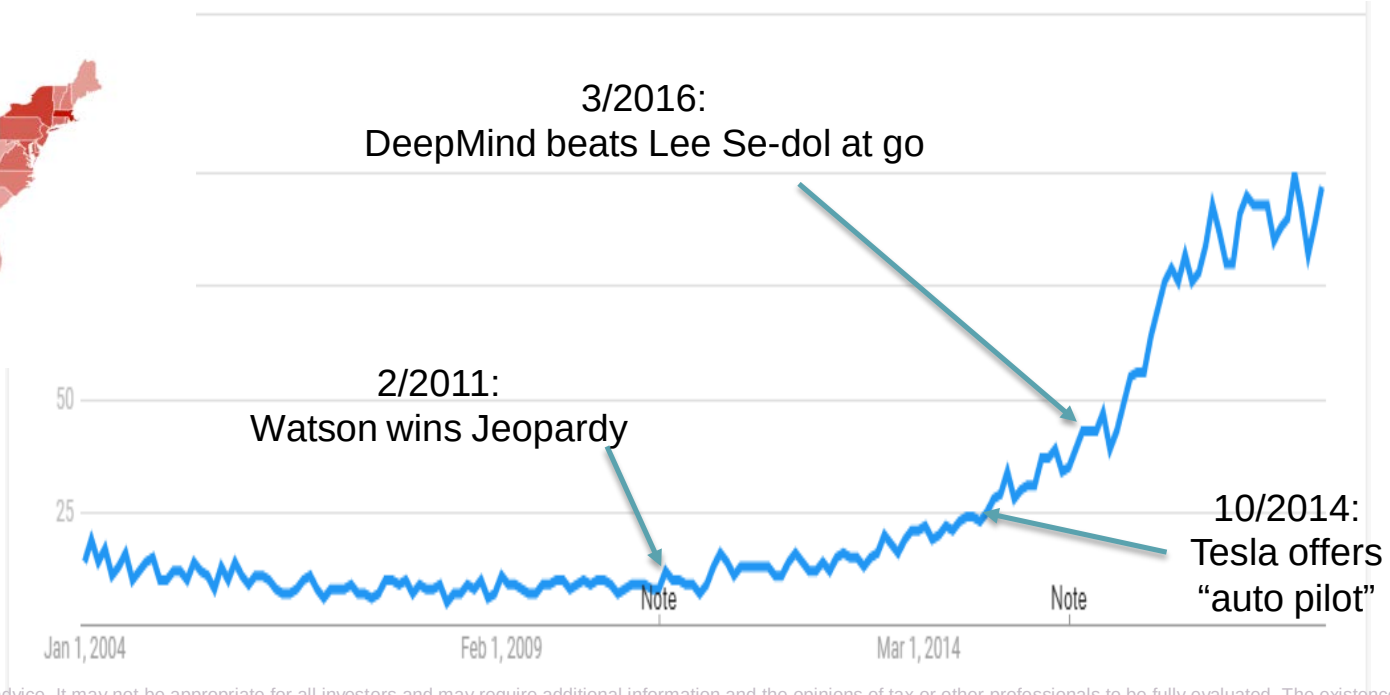
Some Definitions

- **Artificial Intelligence:** Human-like intelligence. The ‘general’ variety is an exciting idea but doesn’t exist yet
- **Machine Learning:** generate classifications, predictions, or relationships between data items in a somewhat self directed way. In recent years established itself in finance.
- **Deep Learning:** as above but also able to identify complex patterns. Modeled after the human brain. Drove many of the (mostly non-finance) breakthroughs in the past decade.



Google Trends “Machine Learning” 1/2004 – 2/2019





A Subjective History of ML in Finance

- **Traditionally, academic finance people have been skeptical**
  - Too easy to over fit
  - Often not driven by structural or at least theoretical models of the world
  - Not easy to interpret
  - Not as well understood as, say linear regressions
- **Practitioners with CS backgrounds led the way**
  - Some (but not many) hedge funds likely began using ML decades ago
  - The typical quant asset manager began sometime in the past 5 years
  - Non-quants aren't there yet but will likely become users
- **ML has now broken through in academic finance as well**
  - See recent papers and conference topics
  - Moritz Zimmermann was a relatively early example
  - Fresh grads now often have a good knowledge base in ML – can be agents of change
- **Progress is closely tied to advances in coding, data, and computational infrastructure**

The History of ML at Geode

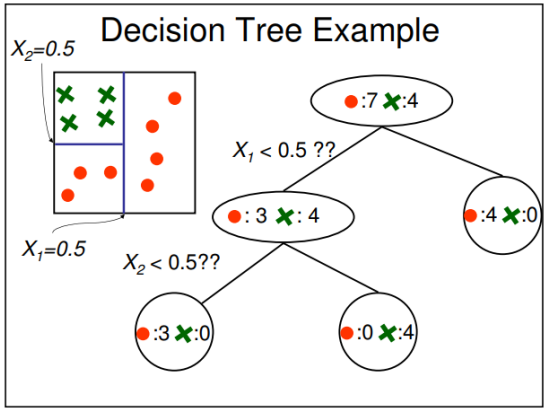
- Started as an experiment led by junior analyst in 2006
- First model, ‘Hal,’ went live in 2007 as an equity market neutral strategy
- Guess what happened in August 2008…
- Subsequently we derisked (bad call) but kept it running (good call) with improvements to risk modelling, risk management and analytics
- A second model was launched in 2014
- Both have been continually improved since then
- Both are among our best performing strategies
- Our current focus is on Neural Networks, uses outside of market neutral equities as well as infrastructure upgrades.

Major Techniques

- **Decision Trees / Random Forests**
- **Neural Networks**
- **SVM: Support Vector Machines**

An Introduction to Random Forests

Key Concepts



- **Decision Tree**: Classifying/Predicting from a set of features
  - Each level splits the data according to different features
  - *Goal*: Achieve good classification with minimal number of decisions

- **Bagging**: (**B**ootstrap **Agg**regation)
  - Replicate the dataset by sampling with replacement
  - Apply a learning method (usually decision tree learning) to each bootstrap sample to produce predictors
  - Use the average of these predictors as the final predictor

- **Random Forests**
  - Do Bagging, but in addition, when growing the tree, select a random sample of features to consider in each step
  - This will lead to very different trees from each bootstrap sample
  - The randomization steps in Bagging and Random Forests will help avoid over-generalization (over-fitting)

From Trees to Forests

Bootstrap sampling

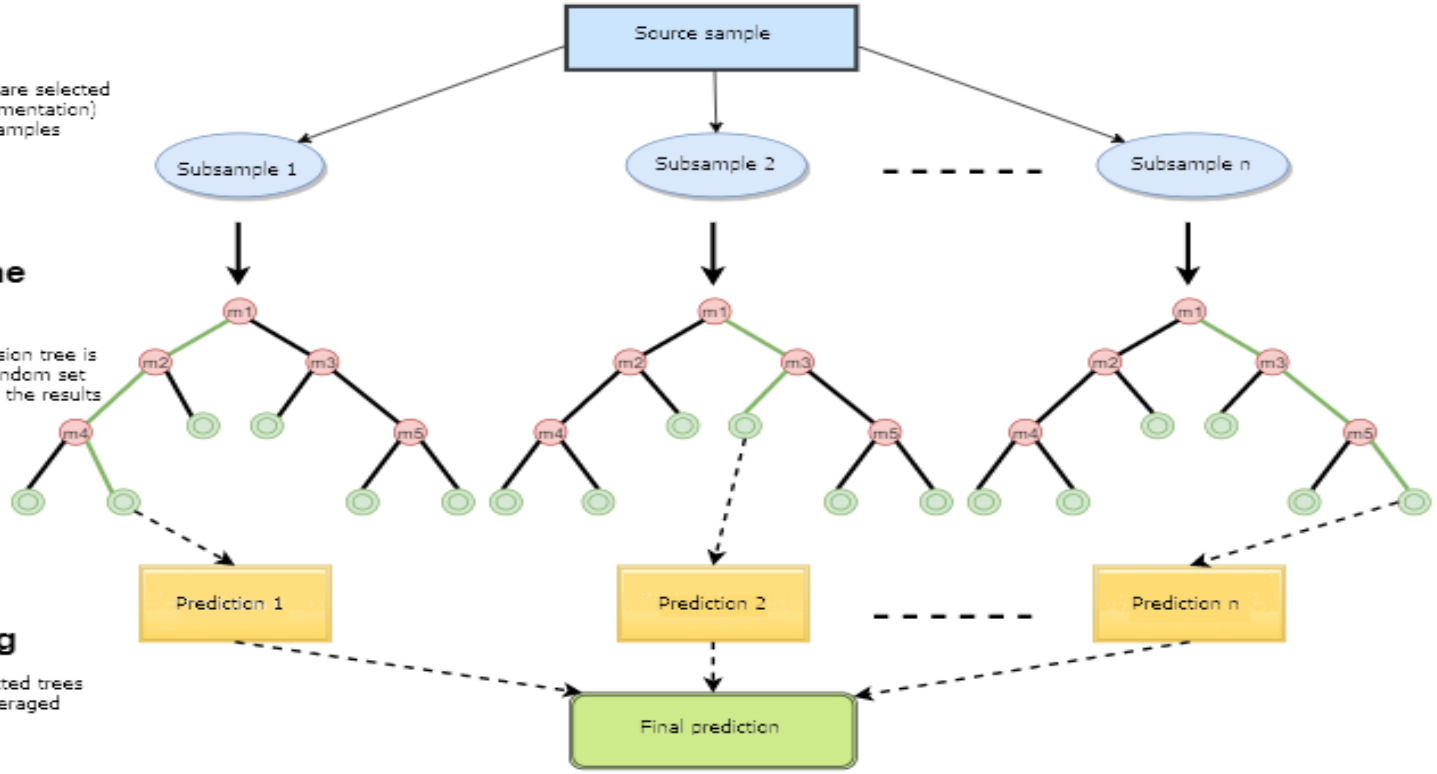
r (percentage) examples are selected (0.63 in classical implementation) in n random subsamples

Building the models

for each subsample, a decision tree is constructed based on a random set of m features (covariants), the results fall into leaves

Bootstrap aggregating

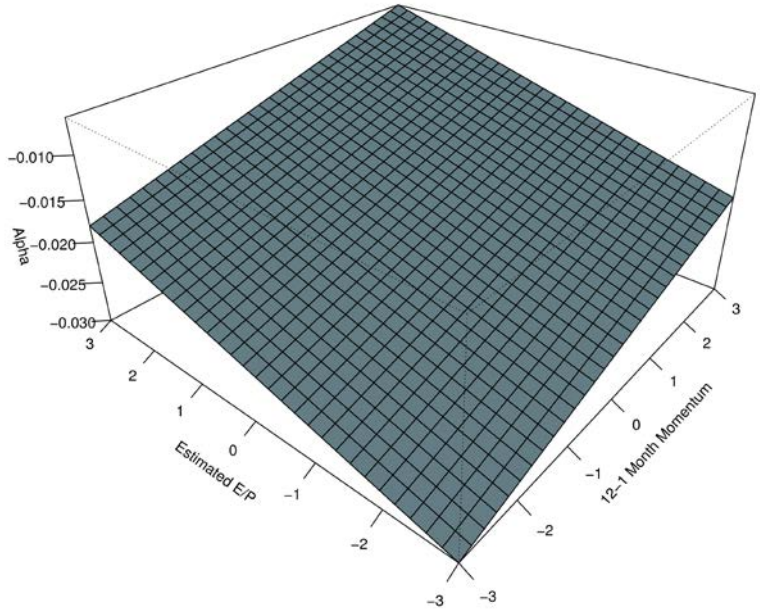
results from all constructed trees are gathered and averaged



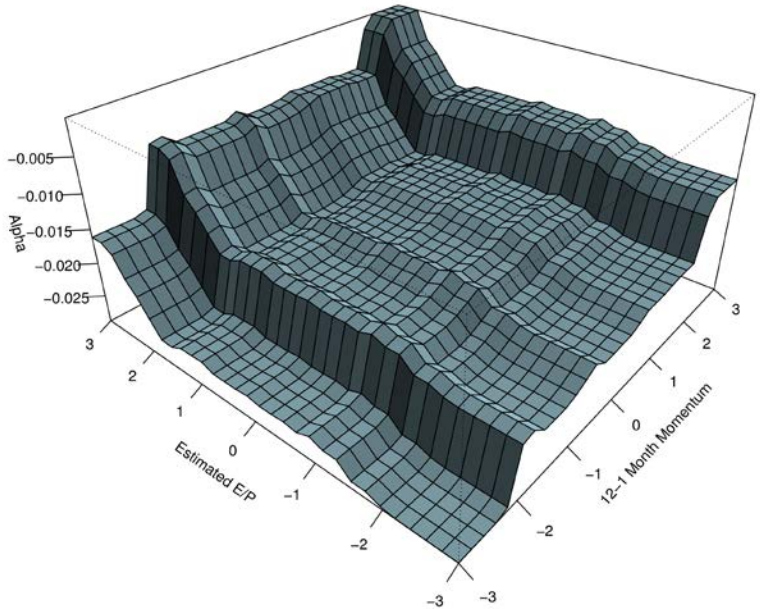
Source: https://www.mql5.com/en/articles/3856

Example: Linear vs Non-Linear (Random Forest Based) Alpha Modeling

Linear Regression

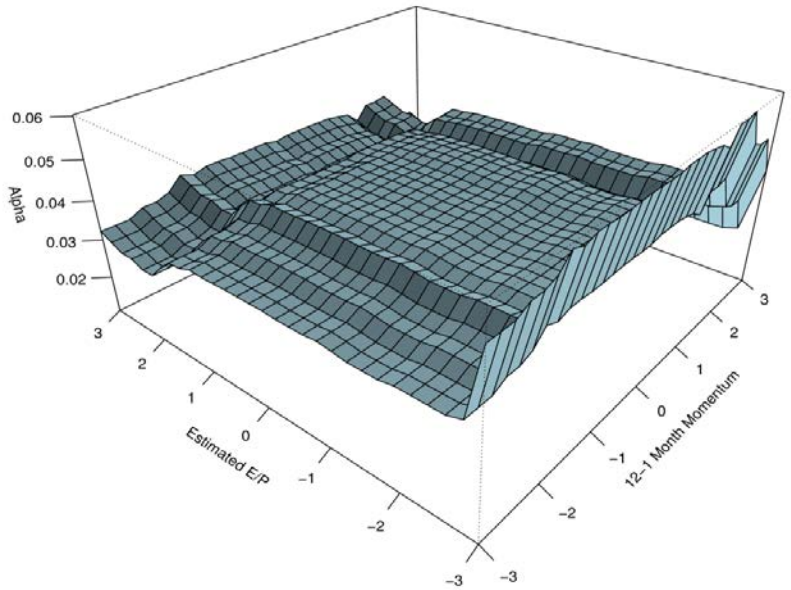


Random Forrest



For illustrative purposes only

Another Example: Dynamic Non-Linear Alpha Modeling



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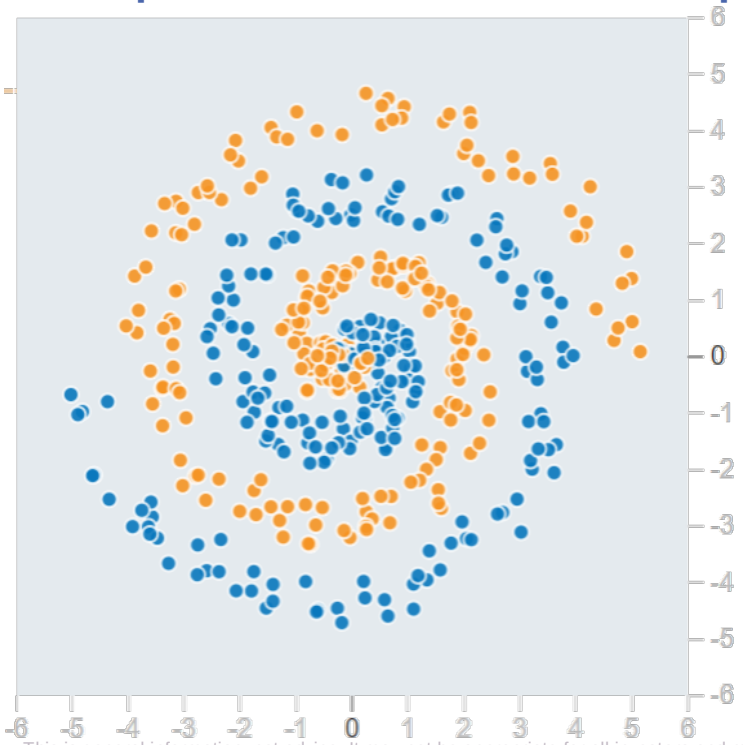
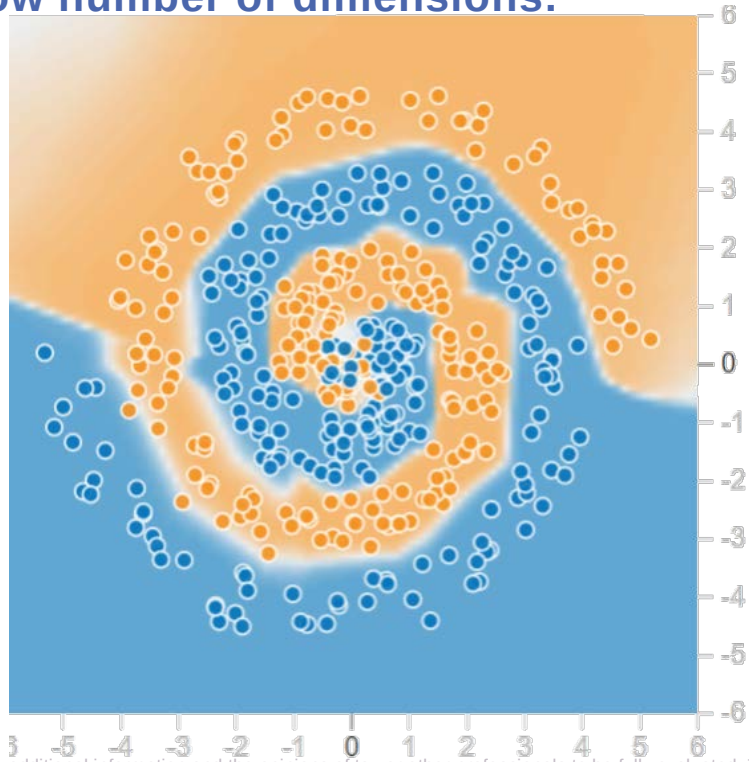
An Introduction to Neural Networks

Neural Networks: Illustration

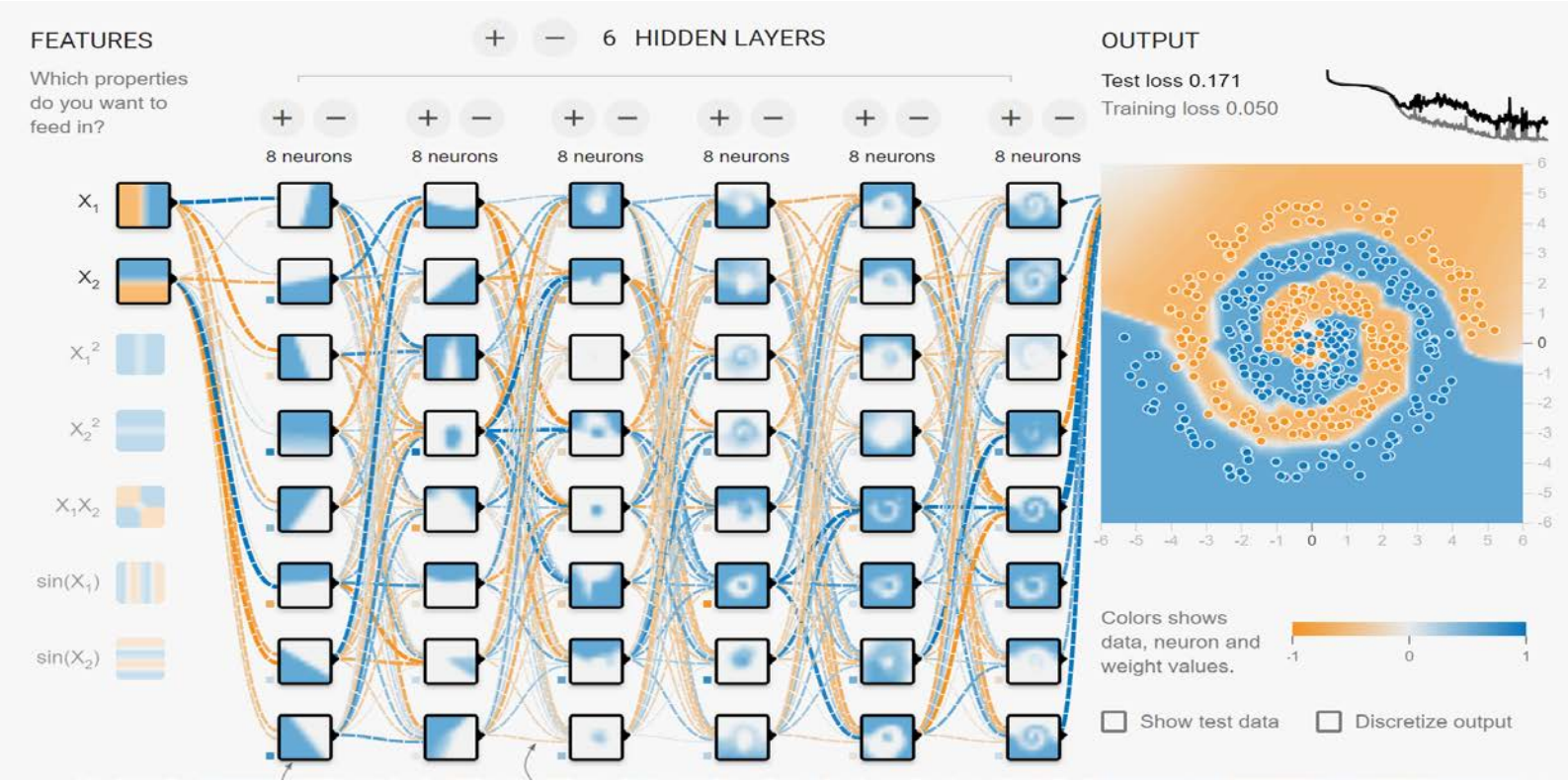
- **Example of nonlinear relationship – low number of dimensions:**





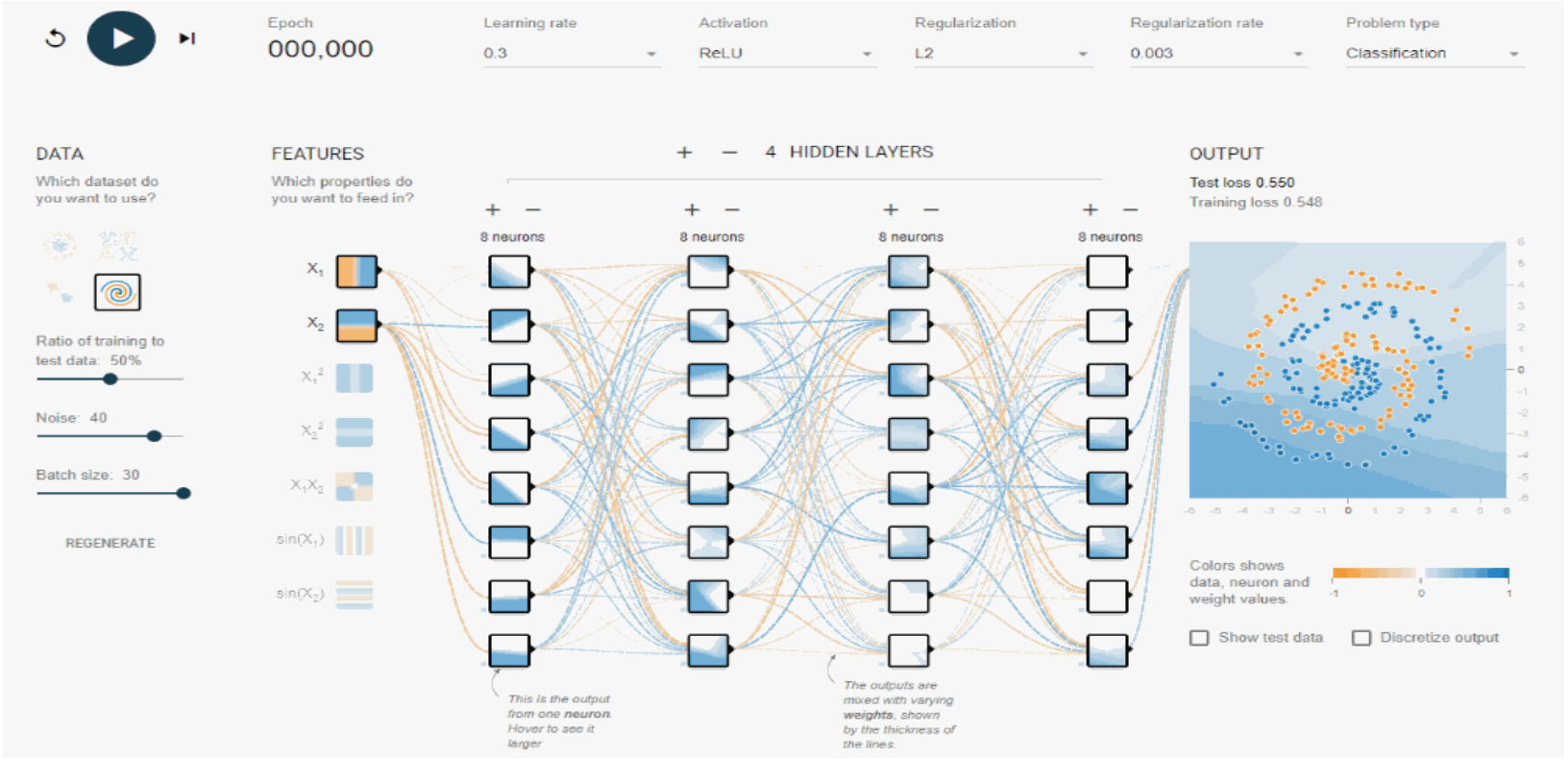
Source: playground.tensorflow.org

Neural Networks: ‘Neurons’ and ‘Layers’



Source: playground.tensorflow.org

An Animated Example: The Learning Process



Source: playground.tensorflow.org

Comparisons;
Technology Needs;
What We've Learned So Far

Linear Regressions RF vs NN

	Linear Regressions	RF	NN
What they Model	Linear additive relationships	Non linear and interactive relationships	Complex Patterns in high dimensionality data
Data Needed	A fair amount	A lot	A ton
Computing Needs	Little	A lot	A ton
Transparency	Well understood, easy to interpret	While trees are intuitive, forests are pretty opaque	Hard to analyze and interpret
Collective Experience	~150 years	Decades	Years

Running *a* Machine Learning Model is Trivial

Linear Regression

R

```r
model <- lm(y ~ ., training_data)
```

Python

```python
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(x, y)
```

Random Forest

R

```r
library(randomForest)

model <- randomForest(y ~ ., training_data)
```

Python

```python
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()
model.fit(x, y)
```

Simple Neural Network *(Tensorflow, Keras, PyTorch, etc. are better-suited for deep learning models)*

R

```r
library(neuralnet)

model <- neuralnet(y ~ ., training_data)
```

Python

```python
from sklearn.neural_network import MLPRegressor

model = MLPRegressor()
model.fit(x, y)
```

…building a good one is harder though

ML and Technology

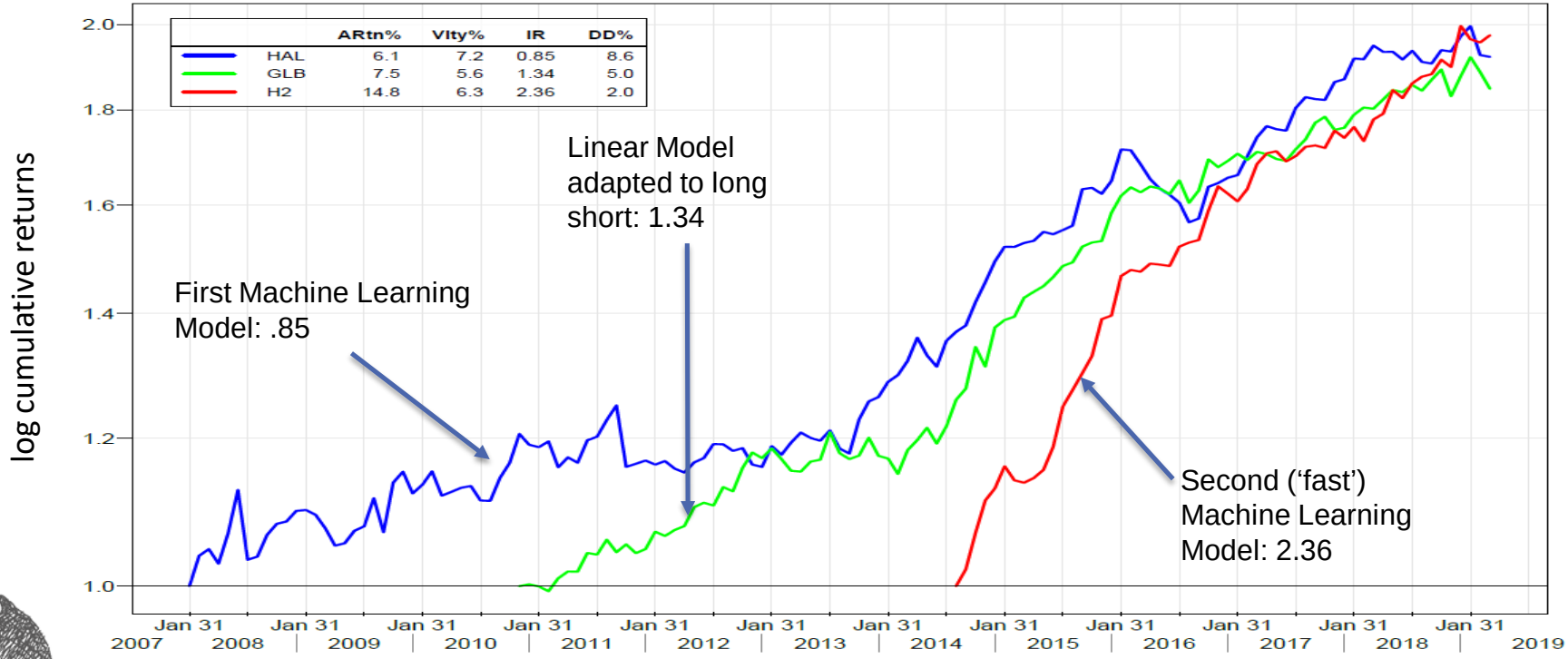
- **ML is enabled by advances in technology**
- **This also means the industry has to keep up and upgrade**
  - Cloud computing, more capacity, more elasticity
  - GPU servers
  - More powerful programming languages. See the rise of Python/TensorFlow/PyTorch
  - Data Management
  - Version control and collaboration tools
  - Visualization tools

Some Key Questions and Selected Learnings

- **Contrary to popular belief, the task of designing and structuring models does not go away. It only becomes more complex**
  - Exactly what are you predicting?
  - Using what as inputs?
  - Time series or X-section?
  - Are relationships static or allowed to change over time?
- **You need to think about if/how to transform the data going in**
- **Tuning!**
- **How to counteract fitting issues!!**
- **ML models can usually handle more inputs than traditional regressions**
- **How to handle Risk Modeling, and the related topics of risk decomposition and attribution is more tricky than in traditional models**

A Real Life Example

Some Live Results*



*HAL: From 2008/01/31 to 2019/03/31, GLB: From 2010/12/31 to 2019/03/31. H2: From 2014/09/30 to 2019/03/31. After t-costs and fixed fees but gross of performance fees

Key Properties

Correlation Coefficients*

		HAL	GLB	H2
Machine Learning #1	HAL	1.00	0.33	0.47
Linear	GLB	**0.33**	1.00	**0.26**
Linear Learning #2	H2	0.47	0.26	1.00

Largely similar inputs but fairly different returns from traditional model

Performance and Betas*

		Return	Vol	IR	Beta
Machine Learning #1	HAL	7.6%	5.6%	1.36	-0.15
Linear	GLB	8.6%	5.8%	1.48	-0.13
Linear Learning #2	H2	14.8%	6.3%	2.36	-0.13

Slightly negative market betas (more for ML models)

The machine is not the only one who is learning

*Measured from 2014/09/30 to 2019/03/31. Returns After t-costs and fixed fees but gross of performance fees

Summary

Summary

- **After a delayed start in main stream finance, Machine Learning has now broken through with a vengeance**
- **Machines are less self-organizing than one might think. Structuring and modeling is still key to good design. Training in traditional statistics helps**
- **The tools and infrastructure are at a point where getting started is quite straightforward – maybe deceptively so**
- **Based on over a decade of live results we are pretty confident Machine Learning – if applied well and to the right problems – works and has further potential**

Thank You

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