Weekly Meeting Notes

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Overview:

- P&L (profit & loss) is a metric used to analyze the effectiveness / profitability of an investment portfolio
- There has been some research in the area that covers P&L using neural networks which is a new approach
- Quantitative researchers find a new analysis for understanding merger arbitrage spreads
- K-means clustering is an unsupervised machine learning approach to clustering
- Within quantitative portfolio management we can use k-means clustering to identify which security to invest in
- Bayesian statistics is one of the widest used probabilistic methods and has tons of application to finance

Quant: Finding Alpha from its Signatures

Key facts

- Quants at JPMorgan working the academic researchers are trying to “signatures” on simulated market data
- They use synthetic data for
    - Machine learning algorithms for option hedging
    - Stress testing, scenario analysis and machine learning training data sets
- Blanka Horvath from King’s College is one of the leading researchers in the area
    - Her team is building a “regime classifier” to adjust options prices

JPMorgan Chase & Co.

Blanka Horvath from King’s College

- Another person working in this area is Maud Lemerceier of the University of Warwick
    - They use a mean reversion parameter in simulated market data to make a distribution regression with signature
    - Mean reversion is used in volatility models: Heston, Dupire, SABR
- The research is being tracked by quants at Citi and Standard Charter, Catley Lakeman Securities
- Some quants think that they can find alpha signals in this by looking at how the coefficients change over time
    - In technical analysis terms this would help them build more rigorous models for head and shoulder patterns
    - The coefficients can possibly be learned by machine learning models which is why they use LSTMs

The concerns

- The computational complexity may to big for most computers
    - The computational time may be to slow or impossible
    - There could be machine learning problems that look at solving this
- The signals are prone to
    - Describing relationships that aren't actually there
- But the general consensus is that buy side and sell side will both benefit from this advancement

What the signature helps solve

- Receiving tick data is hard to work with because you have to view that data as more of a stream and not individual pieces
- Signatures would let you see the data as a path rather than a sequence of point-in-time
- First order signature measure the drift up or down for the sequence
- Second order signatures measure the volatility path
- Higher orders go beyond what can be described
- It also works with data that is missing information

- This could also lead to firms needing less computing power and data storage to maintain all of the information if they can track signatures
- But there is question about going from signatures back to the data
- The main problems that quants have "overfitting"
  - Its when the model can't distinguish between important information and "noise" which is a big problem that plagues unsupervised learning
- The main things that quants want to work out is that signatures may be impossible to compute
  - The way that quants do this is that they usually truncate the signatures into 3 or 4 orders which may lose critical information
  - The loss of critical information may have problems with heavy-tailed data practitioners because they may lose those tail events

Articles:

Risk.net: 'Signatures' promise quants a tool for all jobs here

ArXiv: Distribution Regression for Sequential data here

Risk.net: Synthetic data enters its Cubist phase here

Finance: P&L

Key facts

- Quants are very interested in the future P&L distribution of a portfolio
  - It allows them to manage risk
  - Set aside capital for regulatory reasons
- There are many different types of P&L modelling strategies
  - Parametric modelling
  - Linear and quadratic mapping on risk factors
  - Closed-form analytic approximations

What makes calculating P&L tough

- We may have to use a system of monte carlo simulations that are computationally expensive
- It's much harder to work with when using nonlinear payoffs of path dependent derivatives (American Options)
- The original method was inspired by the least square Monte Carlo (LSM) to estimate via back propagation
- Then came an optimal strategy using polynomial interpolation

Finance: Calculating P&L using Neural Networks

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Quantitative Finance News: Merger Arbitrage Spread

- Versors Investments looked into the merger arbitrage spreads to analyze them.
- During a merger an acquirer purchases a target at a premium usually expressed in share price.
    - That premium is usually higher than the current share price
    - There is an arbitrage possibility by going long on the target and short on the acquirer. When the acquirer pays the premium you swap the shares at a higher price making an arbitrage
    - A key to merger arbitrage is assuming that the deal will be completed
- Market practitioners and other researchers look at the spread (premium - share price) to give them an idea on what will happen

VERSOR

Analyzing the spread

- Historically if the spread is wider, then it is usually a sign that the merger may fail and vice versa
- Another way of thinking about it
    - If investors think that the merger will be completed they'll buy the share hoping to swap it at the premium price
    - As more investors buy the share they push the price up
    - If they didn't think the deal would go through they wouldn't buy the shares

Versor's approach

- They look at around 4,000 between companies based in US, Canada, UK, and Europe mergers and kept track of
    - Probability that the merger will close
    - Determine downside risk
    - Perform competing bid analysis
- Harford (1999) shows that cash rich firms are more likely to attempt acquisitions
- Another thing to consider is that private equity funds have to spend their cash therefore their dry powder has to be used
- Typical failure rates are around 10%

Versor's findings

- They found that 80% of the spread has no usefulness as a predictor of merger success
- They say that 80% the spread encapsulates a series of information
  - region
  - Nature of deal
- They also found that deals done by private equity backers during times of stress tend to fail more often than other deals
- They also found that it is harder to predict success involving a company based in emerging market

Versor's machine learning approach

- Thye use 2 different undisclosed machine learning algorithms to create a forecast
- They also use Natural Language Processing to analyze news and update their database

<u>Articles:</u>

Risk.net: Machines say: 'Ignore the spread in merger arb' here

Versor Investments: The environment for merger arbitrage: 2021 here

Computer Science: K-means Clustering

Overview:

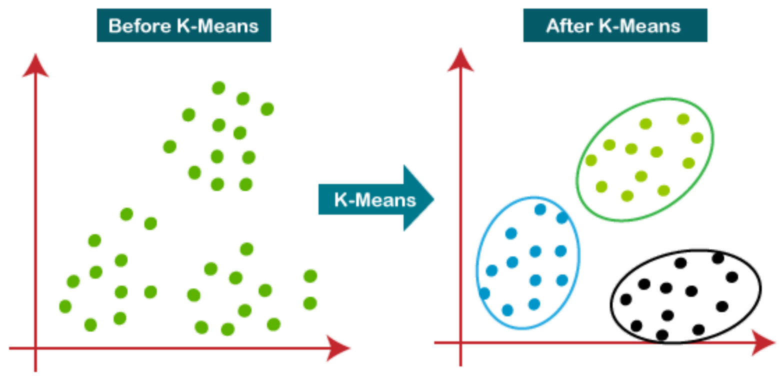
- Clustering algorithm
- Unsupervised learning
- Dimensionality reduction tool

The K-means clustering algorithm is used to find groups which have not been explicitly labeled in the data.

- Easy to apply to even large data sets

- Common data analysis technique to get an intuition about data structure

- Given a set of observations (x1, x2, ..., xn), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k (≤ n) sets S = {S1, S2, ..., Sk}



Sklearn is the most common python package for kmeans

Algorithms:

- Naive k-means: most commonly use it is defining each cluster via the least squared Euclidean Distance

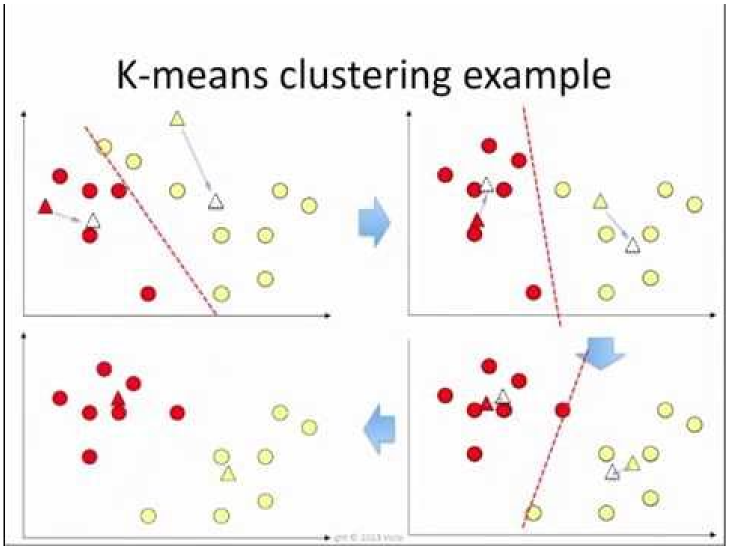
- Hartigan-Wong Method - this locals at finding the local minimum of the the minimum sum-of-squares problems

- Variations only converge to a local minima of minimum-sum-of-squares cluster problem

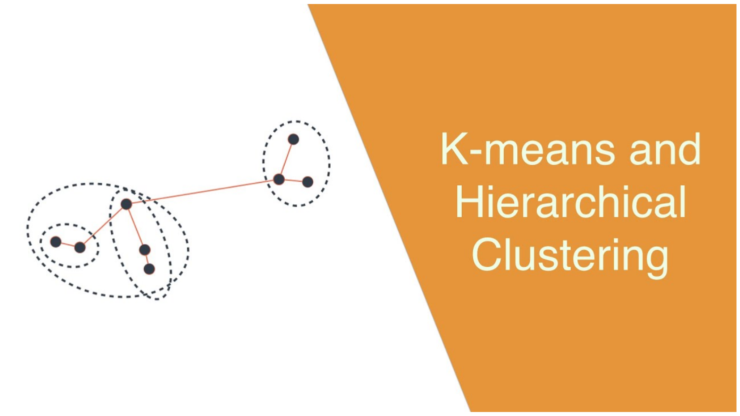
- And there are many other variations

- Standard Naive K-means algorithm alternates between an assignment step and an update step
    - Assignment: assign observations to clusters with nearest mean (euclidean distance)
    - Update: Recalculate means

Victor Lavernko: K-means clustering: how it works



Lusi Serrano: Clustering: K-means and Hierarchical



StatQuest: K-means clustering

Codebasics: Machine Learning Tutorial Python - 13: K Means Clustering Algorithm

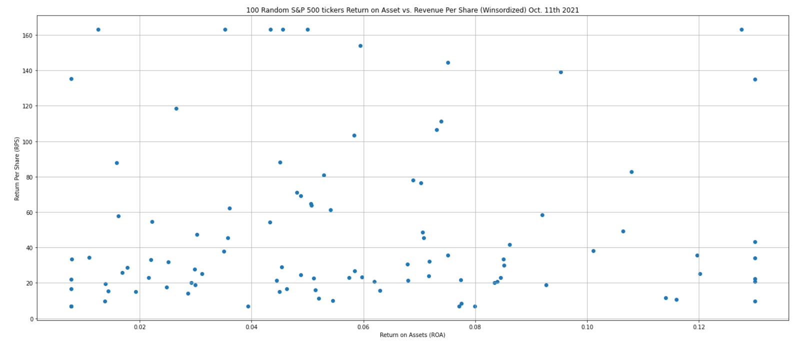
Kmeans clustering file (here)

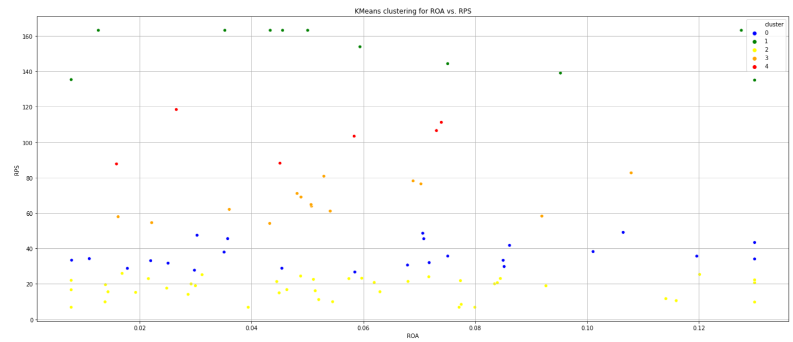
Quant: K-Means clustering allocation

The goal

- Clustering algorithms have ton of application in asset allocation models
- Allocation strategies using clustering algorithms would be
    - Principal component analysis to allocation positions that best “offset” each other or their eigenvectors are orthogonal
    - Kmeans clustering to find best securities that are the best “centroids” for each cluster

Kmeans clustering example





The method used in this example

- The goal of this is to find a way to make a “scatter” plot of each stock. In this case we used
    - Return on Asset = Net Income / Net Assets
    - Return per Share = Revenue / Common Shares
- It can really be any calculation, and with python’s yfinance API they offer a whole list of statistics that we can pull

- In this case we were able to separate the securities and then find which one is best
- The model is good at picking securities, but there isn’t framework for how much to allocate
- Of course that can be solved via any allocation optimization model

Python file:

Data collection file (here)

Kmeans allocation jupyter notebook (here)

Computer Science: Bayesian Statistics

Bayesian inference is a method of statistical inference in which Bayes' theorem is used to update the probability for a hypothesis as more information becomes available.

- The posterior (new) probability is a consequence of two antecedents:
  - A prior (old) probability
  - And a likelihood function

- H is the hypothesis
- P(H) is the prior probability
- P(E | H) is the likelihood function
- E is the evidence corresponding to new data
- P(E) is the model evidence

Bayes' Theorem

$$P(H \mid E) = \frac{P(E \mid H) \cdot P(H)}{P(E)}$$

Although it looks easy, it is one of the cornerstones to probabilistic methods.

- In finance, Bayesian Inference has been applied to problems of prediction such as how changes in interest rates affect the value of an index

- Bayesian probability models for forecasting are liked due to logical rigor, general reliability, and intuition

- Some issues with Bayes:
  - Choice of prior takes work
  - Models involving many variables are computationally intensive
  - Posterior distributions are difficult to incorporate
  - Predictions are not always precise (there is room for error)

Bayesian statistics notebook (here)

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