BA870: Topics in Financial & Accounting Analytics

Lecture #11 (Tuesday, April 26, 2022)

Professor Peter Wysocki

Topics: AI and Ethics and Bias; Time Series Analysis for Stock Prices

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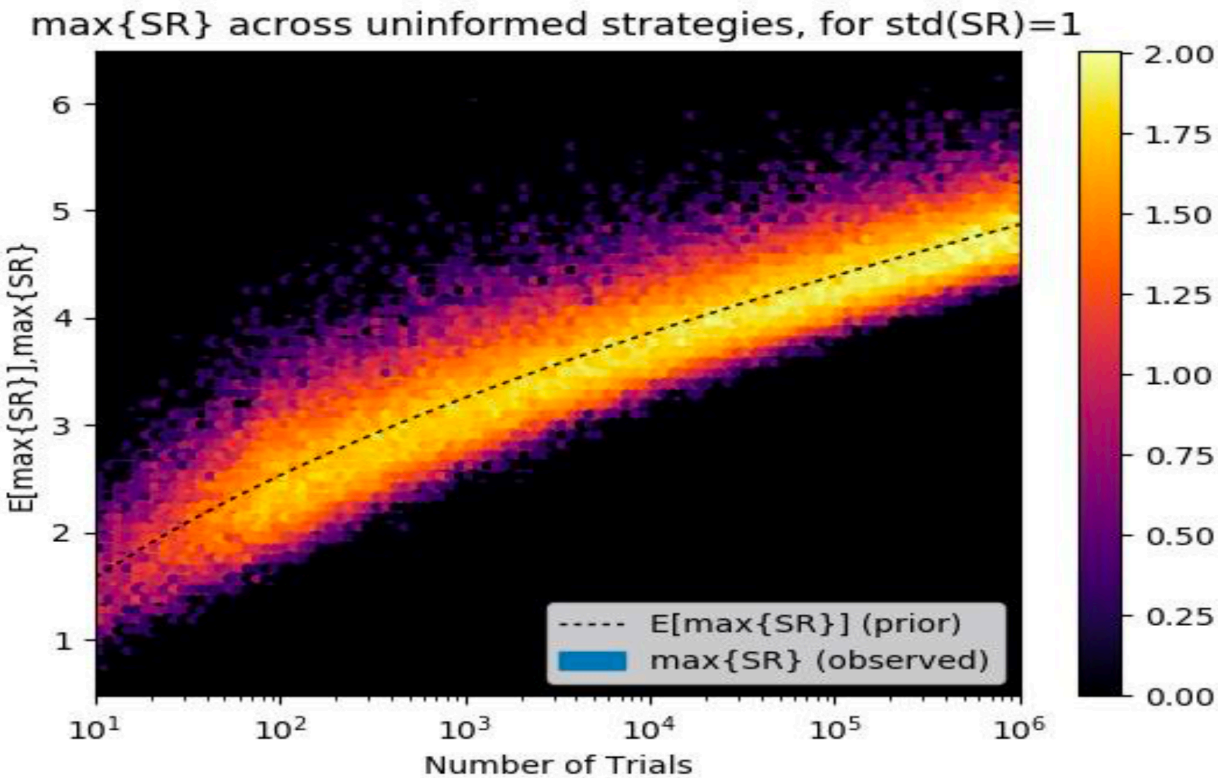
The Most Important Plot In Finance



The y-axis displays the distribution of the maximum Sharpe ratios (max{SR}) for a given number of trials (x-axis). A lighter color indicates a higher probability of obtaining that result, and the dash-line indicates the expected value. For example, after only 1,000 independent backtests, the expected maximum Sharpe ratio (E[max{SR}]) is 3.26, even if the true Sharpe ratio of the strategy is zero!

The reason is *Backtest Overfitting*: When selection bias (picking the best result) takes place under multiple testing (running many alternative configurations), that backtest is likely to be a false discovery. **Most quantitative firms invest in false discoveries**.

From Marcos Lopez De Prado: https://ssrn.com/abstract=3447398

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Problems with “Data Mining” to Find Investment Strategies

- With Backtesting, you can find strategies that work in the past (High Sharpe Ratio).
- But High Past Sharpe Ratio is typically unrelated to Future Sharpe Ratio!

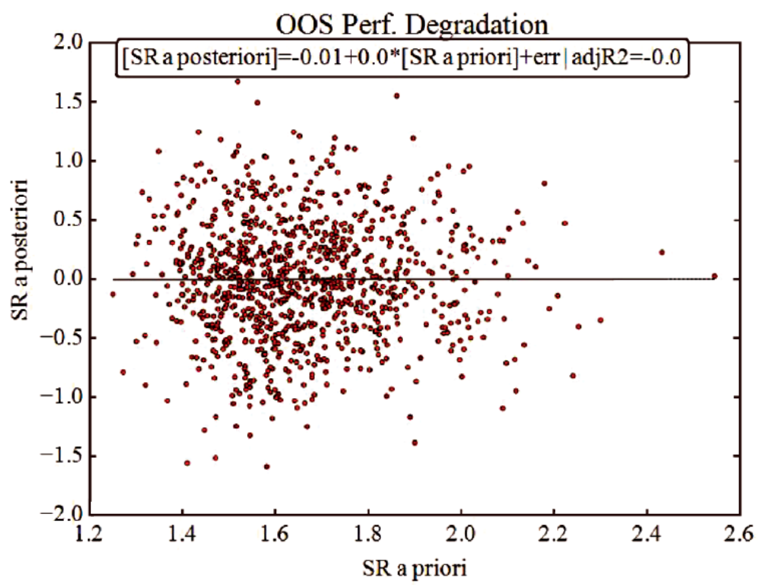

Figure 5. Performance degradation after introducing strategy selection in absence of compensation effects.

Problems with “Data Mining” to Find Investment Strategies

- If investment returns have autoregressive properties, then it even worse.
- Searching for high past Sharpe ratios will lead to negative performance of a strategy in the future!

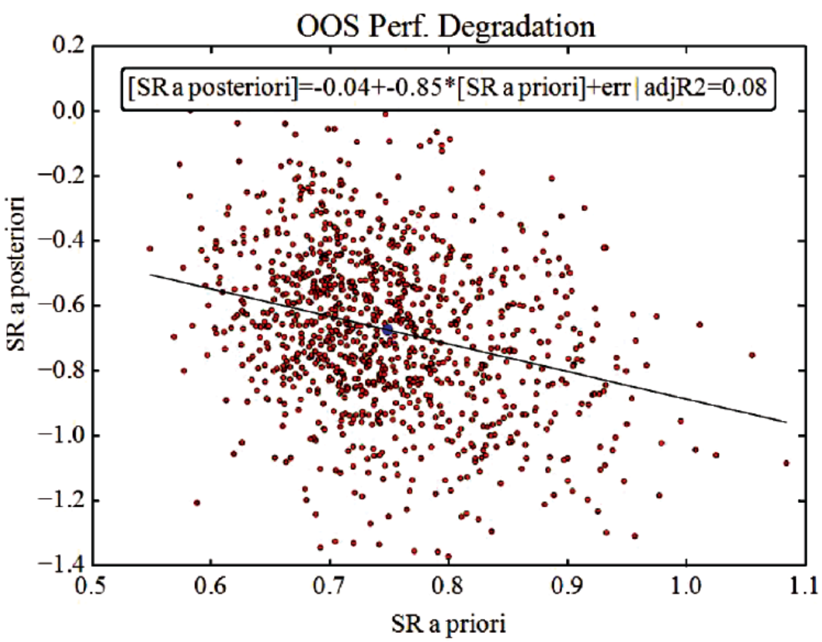

Figure 7. Performance degradation as a result of strategy selection under compensation effects (first-order serial correlation).

a global constraint. If we rerun the previous Monte Carlo experiment, this time for the autoregressive process with $\mu = 0, \sigma = 1, \varphi = 0.995$, and plot the pairs of performance IS vs. OOS, we obtain Figure 7.

The p-values associated with the intercept and the IS performance (SR a priori) are respectively 0.4513 and 0, confirming that the negative linear relation between IS and OOS Sharpe ratios is again statistically significant. Such serial correlation is a well-known statistical feature, present in the performance of most hedge fund strategies. Proposition 5 is proved in the appendix.

Proposition 5. *Given two alternative configurations (A and B) of the same model, where* $\sigma_{IS}^{A} = \sigma_{OOS}^{A} = \sigma_{IS}^{B} = \sigma_{OOS}^{B}$ *and the performance series follows the same first-order autoregressive stationary process,*

$$SR_{IS}^{A} > SR_{IS}^{B} \Leftrightarrow SR_{OOS}^{A} < SR_{OOS}^{B}. \tag{13}$$

Proposition 5 reaches the same conclusion as Proposition 3 (a compensation effect) without requiring a global constraint.

Ethics and Bias in Machine Learning

The three major US credit bureaus, Experian, TransUnion, and Equifax, providing credit scoring for millions of individuals, are often discordant.

In a study of 500,000 records, 29% of consumers received credit scores that differ by at least fifty points between credit bureaus, a difference that may mean tens of thousands dollars over the life of a mortgage [CRS+16].

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Ethics and Bias in Analytics

Big data is algorithmic, therefore it cannot be biased! And yet…

- All traditional evils of social discrimination, and many new ones, exhibit themselves in the big data ecosystem
- Because of its tremendous **power**, massive data analysis must be used **responsibly**
- Technology alone won't do: also need **policy**, **user involvement** and **education** efforts

Ethics and Bias in Analytics – Sources of Data Bias

1. **Data is a social mirror.**

   If training data reflects existing social biases against a minority, the algorithm is going to incorporate it.

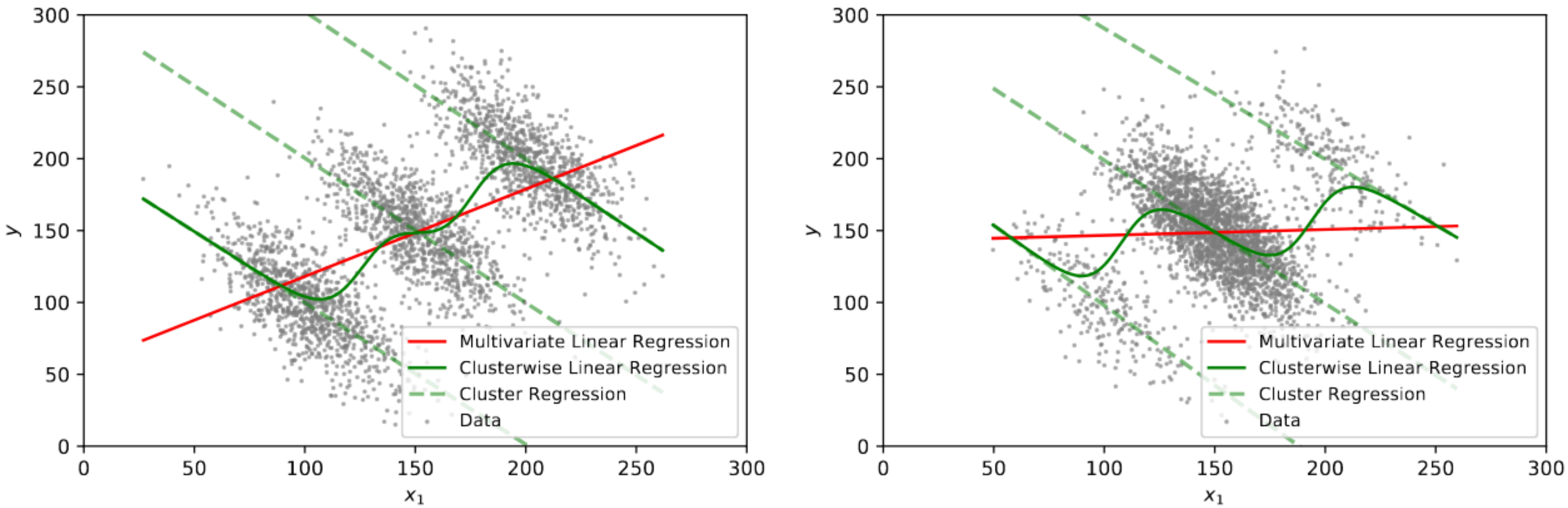
2. **The sample size disparity.**

   Less data available about minorities – models of minorities tend to be worse than those of the general population.

3. **Cultural differences.**

   The statistical patterns that apply to the majority might be invalid within a minority group. A variable positively correlated with the target in the general population might be negatively correlated in a minority group – diverse names in ethnic groups.

Ethics and Bias in Machine Learning – Algorithmic Bias Reduction



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Ethics and Bias in Analytics – Data Bias Reduction

The data bias can be reduced by:

- gathering more data from different sources, thus avoiding sampling bias.
- removing variables in data associated with bias, e.g. age, sex, etc.
- talking to domain experts, where ML systems will be used, in order to get more information.

Ethics and Bias in Analytics: Algorithmic Bias

First definition of the term algorithmic bias in the literature:

Def: *computer systems that systematically and unfairly discriminate against certain individuals or groups of individuals in favor of others.*

Ethics and Bias in Analytics: Algorithmic Bias

- encompasses data bias.
- leads to discrimination and unfairness.
- is introduced during the development and testing stage.
- is produced by human/programmer cognitive biases.
- has unintentional nature.

Ethics and Bias in Analytics: Algorithmic Bias Reduction

- first identify it – talk to domain experts, where ML systems will be used, to get more information.
- introduce de-biasing algorithms and use de-biased datasets.
- perform external auditing and apply special regulations.
- increase algorithmic transparency.

Ethics and Bias in Analytics: Analytics Models and AI Interpretability

- **Non-mathematical definition**:

  Interpretability is the degree to which a human can understand the cause of a decision.*

- **Mathematical (algorithmic) definition**:

  *Interpretability is the degree to which a human can consistently predict the model's result**.*

- It is closely related to AI transparency.
- Algorithmic explanation is more related to individual predictions.

Ethics and Bias in Analytics: Analytics and AI Interpretability

Algorithmic **interpretability/explainability**:

- is especially important for automatic medical diagnostic software.
- relates to the legitimacy of decisions in social/business systems.
- leads to **Accuracy vs. Explainability tradeoff** in various fields of applications.

Ethics and Bias in Analytics: Principles of Algorithmic Accountability

1. **Responsibility**

   Who is responsible, if users are harmed?

2. **Explainability**

   How much of the algorithm code and data will be disclosed?

3. **Accuracy**

   Sources of error and their effect? Worst case scenario?

4. **Auditability**

   Public audit? Communication with outside parties?

5. **Fairness**

   Potential damages to different (social) groups by your algorithms?

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Ethics and Bias in Analytics: What Are The Consequences?

Ethically complicated cases of ML algorithms:

- gender-biased results (**discrimination**)
- racist outcome – classification of black people as „gorillas" (**discrimination**, **fairness**)
- resume filtering based on age and sex in HR industries (**discrimination, fairness**)
- invisible calculation of credit score (**transparency, accountability**)
- data brokers (**confidentiality**)
- Uber taxis price forming (**transparency, fairness**)
- predictive policing (**discrimination**, **fairness**)
- personal and psychological profiling (**privacy, discrimination, confidentiality**)

Ethics and Bias in Analytics: What Are The Consequences?

What can happen, if we **do not oppose biases** in ML systems?

- Businesses will use biased datasets for greater profits.
- ML developers will apply evaluation metrics which can amplify biases – gender or race specific.
- The wide application of ML algorithms will strengthen bias and polarization in society.
- Social tension and distrust to AI and technologies will arise.

Ethics and Bias in Machine Learning – Examples

Bias in online recruitment tools

Online retailer Amazon, whose global workforce is 60 percent male and where men hold 74 percent of the company's managerial positions, recently discontinued use of a recruiting algorithm after discovering gender bias.[9] The data that engineers used to create the algorithm were derived from the resumes submitted to Amazon over a 10-year period, which were predominantly from white males. The algorithm was taught to recognize word patterns in the resumes, rather than relevant skill sets, and these data were benchmarked against the company's predominantly male engineering department to determine an applicant's fit. As a result, the AI software penalized any resume that contained the word "women's" in the text and downgraded the resumes of women who attended women's colleges, resulting in gender bias.[10]

Ethics and Bias in Machine Learning – Examples

But in the biggest ever study of real-world mortgage data, economists Laura Blattner at Stanford University and Scott Nelson at the University of Chicago show that differences in mortgage approval between minority and majority groups is not just down to bias, but to the fact that minority and low-income groups have less data in their credit histories.

This means that when this data is used to calculate a credit score and this credit score used to make a prediction on loan default, then that prediction will be less precise. It is this lack of precision that leads to inequality, not just bias.

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Ethics and Bias in Machine Learning – Examples

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ARTIFICIAL INTELLIGENCE

Bias isn’t the only problem with credit scores—and no, AI can’t help

The biggest-ever study of real people’s mortgage data shows that predictive tools used to approve or reject loans are less accurate for minorities.

By Will Douglas Heaven June 17, 2021

Ethics and Bias in Machine Learning – Examples

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Ethics and Bias in Machine Learning – Examples

Figure 3. Organizations' progress across most ethical dimensions is either modest or non-existent

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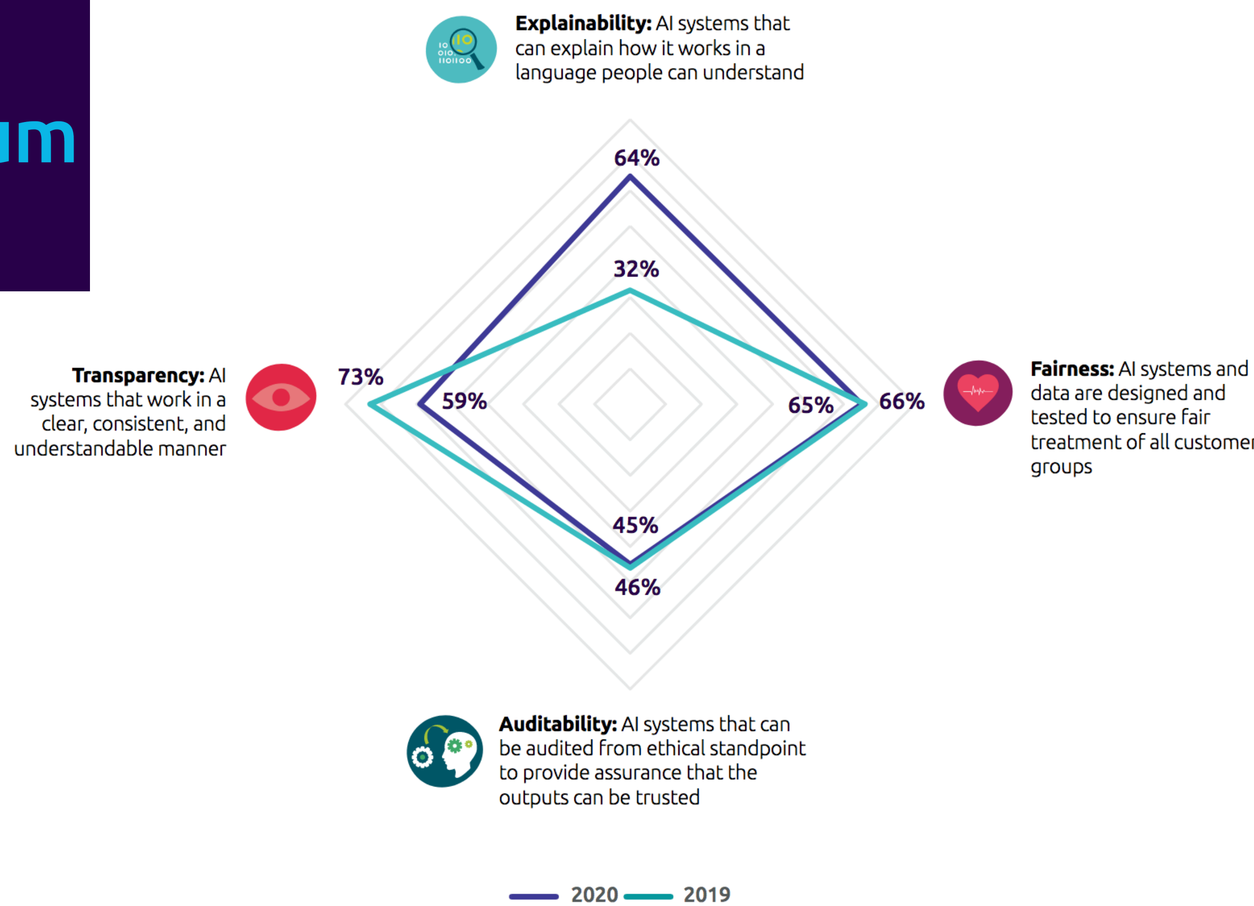
AI and the Ethical Conundrum

How organizations can build ethically robust AI systems and gain trust

Organizations have progressed on explainability but progress is disappointing in certain other ethics dimensions



Ethics and Bias in Analytics

The COMPAS score (Correctional Offender Management Profiling for Alternative Sanctions)

A 137-questions questionnaire and a predictive model for “risk of crime recidivism.” The model is a proprietary secret of Northpointe, Inc.

The data journalists at propublica.org have shown that

- the prediction accuracy of recidivism is rather low (around 60%)
- the model has a strong ethnic bias
  - blacks who did not reoffend are classified as high risk twice as much as whites who did not reoffend
  - whites who did reoffend were classified as low risk twice as much as blacks who did reoffend.

Ethics and Bias in Analytics

During the 1970s and 1980s, St. George's Hospital Medical School in London used a computer program for initial screening of job applicants.

The program used information from applicants' forms, which contained no reference to ethnicity.

The program was found to unfairly discriminate against female applicants and ethnic minorities (inferred from surnames and place of birth), less likely to be selected for interview [LM88].

Ethics and Bias in Analytics

In a recent paper at SIGKDD 2016 [RSG16] the authors show how an accurate but untrustworthy classifier may result from an accidental bias in the training data.

In a task of discriminating wolves from huskies in a dataset of images, the resulting deep learning model is shown to classify a wolf in a picture based solely on …

Ethics and Bias in Analytics

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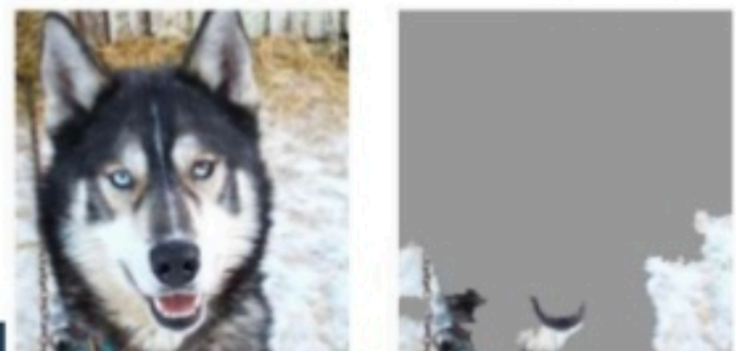
In a task of discriminating wolves from huskies in a dataset of images, the resulting deep learning model is shown to classify a wolf in a picture based solely on ... **the presence of snow in the background!**

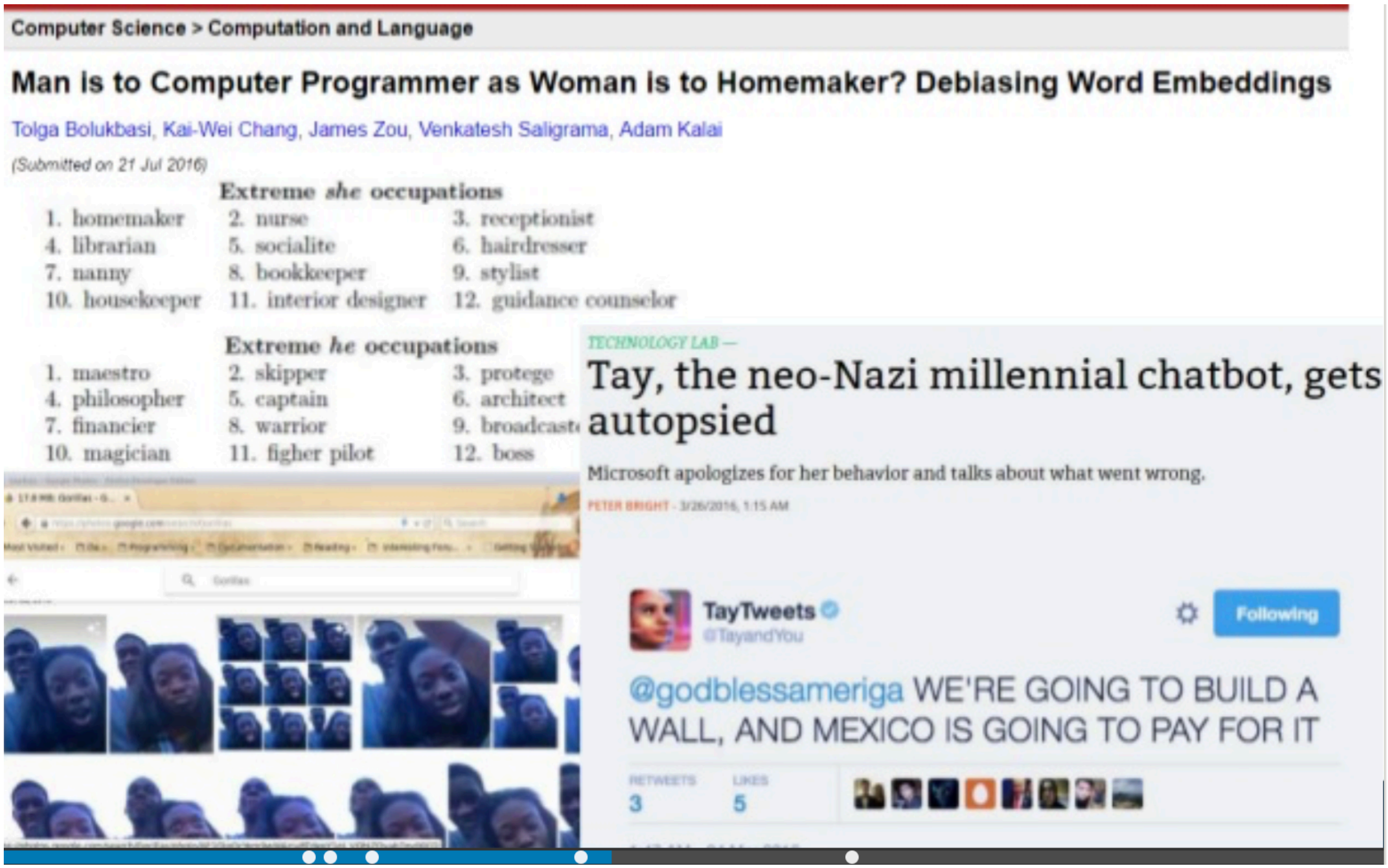
[RSG16] "Why Should I Trust You?" Explaining the Predictions of Any Classifier

SIGKDD 2016 Conference Paper



(a) Husky classified as wolf (b) Explanation

Ethics and Bias in Analytics



Ethics and Bias in Analytics and AI

Satya Nadella's rules for AI

www.theverge.com/2016/6/29/12057516/satya-nadella-ai-robot-laws

- **AI must be designed to assist humanity.** Nadella says that machines that work alongside humans should do "dangerous work like mining" but still "respect human autonomy."
- **AI must be transparent.** "We want not just intelligent machines but intelligible machines," says Nadella. "People should have an understanding of how the technology sees and analyzes the world."
- **AI must maximize efficiencies without destroying the dignity of people.** "We need broader, deeper, and more diverse engagement of populations in the design of these systems. The tech industry should not dictate the values and virtues of this future."
- **AI must be designed for intelligent privacy.** Nadella asks for "sophisticated protections that secure personal and group information."
- **AI must have algorithmic accountability.** So that "humans can undo unintended harm."
- **AI must guard against bias.** "Proper and representative research" should be used to make sure AI doesn't discriminate against people (like humans do).

Notes on Predicting Stock Returns Using Time Series Analysis: What is a Stochastic Process?

- **Stochastic (Random) Process:** collection of random variables ordered in time.

- Let **Y** a random variable, $\mathbf{Y_{t,}}$ (e.g. Stock Price or ESG Value such as Environemental Intensity).
- Example: Let **Y** represent the stock price., then Y_1, Y_2, Y_3, etc measures the stock price over time.

Stochastic Processes

- **Stationary Stochastic Processes:** A stochastic process is said to be **stationary/ weakly /covariance/2nd-order stationary** if:

- Its **mean** and **variance** are constant over time, and
- The value of the **covariance** between the two time periods depends only on the distance/lag between the two time periods and not the actual time at which the covariance is computed.
- E.g. let's $\mathbf{Y_t}$ be a stochastic process, then;

- **Mean:** $E(Y_t) = \mu$ .... (1)
- **Variance:** $\text{var}(Y_t) = E(Y_t - \mu)^2 = \sigma^2$ .... (2)
- **Covariance:** $\gamma_k = E[(Y_t - \mu)(Y_{t+k} - \mu)]$ .... (3)

Why are Stationary Time Series so Important?

- If a time series is **non-stationary**, we can study its behavior only for the time period under consideration, and as a consequence, it is not possible to generalize it to other time periods.
- Therefore, for the purpose of forecasting, such (non-stationary) time series may be of little practical value.
- **Non-stationary Stochastic Processes:** Although our interest is in stationary time series, one often encounters **non-stationary time series**
- A **non-stationary time series** will have a time-varying mean or a time-varying variance or both.

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Random Walk Model (RWM) – Stock Prices

- The classic example of non-stationary time series is the Random Walk Model (RWM).
- It is often said that asset prices, such as stock prices or exchange rates, follow a random walk (i.e. non-stationary).
- **Types of Random Walks:**
  a) **Random Walk Without Drift:**
     i.e. no constant/intercept term and
  b) **Random Walk With Drift**
     i.e. a constant term is present

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Random Walk without Drift

- The time series $\mathbf{Y_t}$ is said to be a random walk without drift, if

$$\mathbf{Y_t = Y_{t-1} + u_t} \;\ldots\ldots\ldots\;(4)$$

- Here, the value of Y at time **(t)** is equal to its value at time $(t - 1)$ plus a random shock; thus it is an AR(1) model.
- Believers in the **Efficient Capital Market Hypothesis** argue that stock prices are essentially random and therefore there is no scope for profitable speculation in the stock market:
- If one could predict tomorrow's price on the basis of today's price, we would all be millionaires.

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Take the Difference!

- Now, if you write $Y_t = Y_{t-1} + u_t$..... (4) as

$$(Y_t - Y_{t-1}) = \Delta Y_t = u_t \;.......$$

It shows that, while Y_t is non-stationary, its 1st difference is stationary.

- In other words, the 1st differences of a random walk time series are stationary.

The Phenomenon of Spurious Regression

- **Stationary Time Series** are important, consider the following two random walk models:

$$Y_t = Y_{t-1} + u_t \quad \ldots\ldots\ldots\ldots\ldots$$

$$X_t = X_{t-1} + v_t \quad \ldots\ldots\ldots\ldots\ldots$$

- Where we generated 500 observations of $\mathbf{u_t}$ from $\mathbf{u_t \sim N(0, 1)}$ and 500 observations of $\mathbf{v_t}$ from $\mathbf{v_t \sim N(0, 1)}$ and assumed that the initial values of both **Y** and **X** were zero.
- We also assumed that $\mathbf{u_t}$ and $\mathbf{v_t}$ are serially uncorrelated as well as mutually uncorrelated.
- Both these time series are non-stationary; i.e. they are **I(1)** or exhibit stochastic trends.

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Spurious Regressions

- Suppose we regress $\mathbf{Y_t}$ on $\mathbf{X_t}$.
- Since $\mathbf{Y_t}$ and $\mathbf{X_t}$ are uncorrelated I(1) processes, the R^2 from the regression of **Y** on **X** should tend to zero; that is, there should not be any relationship between the two variables.
- But wait till you see the regression results:

Variable	Coefficient	Std. error	t statistic
C	-13.2556	0.6203	-21.36856
X	0.3376	0.0443	7.61223

$R^2 = 0.1044 \quad d = 0.0121$

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Tests of Stationarity

- In practice we face two important questions:
- How do we find out if a given time series is stationary or not?
- Is there a way that it can be made stationary?
- Prominently discussed tests in the literature are:
- Graphical Analysis
- The Unit Root Test

Graphical Analysis

- Before pursuing a formal test, it is always advisable to plot the time series under study
- E.g. take the stock price time series.
- You will often see that over the period of study, stock prices tend to be increasing (i.e. showing an upward trend)
- This perhaps suggests that stock prices are not stationary.

The Unit Root Test

- The widely popular test of stationarity is the unit root test.
- We start with: $Y_t = \rho Y_{t-1} + u_t \qquad -1 \leq \rho \leq 1 \qquad (1.1)$

  Where $\mathbf{u_t}$ is a white noise error term.
- We know that if $\rho = 1$ (i.e. in the case of the unit root) (1.1) becomes a **R**andom **W**alk **M**odel **W**ithout **D**rift, (a non-stationary stochastic process).
- Therefore, why not simply regress $\mathbf{Y_t}$ on its lagged value $\mathbf{Y_{t-1}}$ and find out if the estimated ρ is statistically equal to 1? If it is, then Y_t is non-stationary.

The Unit Root Test – How to implement

- Procedure:

$$Y_t = \rho Y_{t-1} + u_t$$

=> $Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + u_t$

=> $Y_t - Y_{t-1} = Y_{t-1}(\rho - 1) + u_t$ or

=> $Y_t - Y_{t-1} = (\rho - 1)Y_{t-1} + u_t$

which can be alternatively written as:

=> $\Delta Y_t = \delta Y_{t-1} + u_t$

where $\delta = (\rho - 1)$ and Δ= first-difference $(Y_t - Y_{t-1})$

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The Unit Root Test

- Hence, to estimate and test the H0: $\delta = 0$.
- If $\delta = 0$, then $\rho = 1$ (i.e. unit root/time series under consideration is non-stationary) and test will become $\Delta Yt = (Yt - Y_{t-1}) = u_t$
- Since u_t is a white noise error term, it is stationary, which means that the first differences of a random walk time series are stationary.
- Now let's turn to the estimation of the test.

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The Unit Root Test

- We have to take the first differences of Y_t and regress them on Y_{t-1} and see if the estimated slope co-efficient in this regression (δ) is zero or not.
- If it is zero, we conclude that $\mathbf{Y_t}$ is non-stationary.
- But if it is negative, we conclude that $\mathbf{Y_t}$ is stationary.
- The only question is which test we use to find out if the estimated co-efficient of Y_{t-1} in is zero or not?
- Unfortunately, under the null hypothesis that $\delta = 0$ (i.e., $\rho = 1$), the **t value** of the estimated coefficient of Y_{t-1} does not follow the **t distribution** even in large samples; i.e. it does not have an asymptotic normal distribution.

Dickey Fuller Test

- Dickey and Fuller have shown that under the null hypothesis that $\delta = 0$, the estimated t-value of the coefficient of Y_{t-1} in follows the **τ (tau)** statistic.
- These authors have computed the critical values of the **tau statistic** on the basis of Monte Carlo simulations.
- Interestingly, if the hypothesis that $\boldsymbol{\delta = 0}$ is rejected (i.e. the time series is stationary), we can use the usual **t test**.

- Y_t is a random walk: $Y_t = \delta Y_{t-1} + u_t$
- Y_t is a random walk with drift: $Y_t = \beta_1 + \delta Y_{t-1} + u_t$
- Yt is a random walk with drift around a stochastic trend: $Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t$

  Where **t** is the time or trend variable.

Dickey-Fuller Test for Stationarity

The test is based on the following regression. The coefficient on the lagged level variable is then used to test if it equals zero, in the same way as a t-test:

$$\Delta y_t = \beta y_{t-1} + u_t$$

Dickey-Fuller Test

- The test statistic does not follow the t-distribution, the critical values have been produced specifically for this test.
- A constant and trend could also be included in this test, the test statistic would still be the test for whether the coefficient on the lagged level variable equals zero
- <u>**In this case the test is for a unit root against no unit root, i.e. the variable needs to be differenced once to induce stationarity.**</u>

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Augmented Dickey-Fuller Test (ADF)

- The error term in the Dickey-Fuller test usually has autocorrelation, which needs to be removed if the result is to be valid. The main way is to add lagged dependent variables until the autocorrelation has been mopped up.
- The test is the same as before in that it is the coefficient on the lagged dependent variable that is tested.

Augmented Dickey-Fuller Test

The test is as follows, where the number of lagged dependent variables is determined by an information criteria:

$$\Delta y_t = \beta y_{t-1} + \sum_{i=0}^{N} \Delta y_{t-i} + u_t$$

Conclusion

- The Dickey-Fuller or Augmented Dickey-Fuller tests test for stationarity, based on the test for a random walk.
- If not stationary, you should difference your data for analysis.