Why is your data valuable? A machine learning and AI perspective

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Tampere University of Technology

MyData2016 - 2 September 2016

Outline

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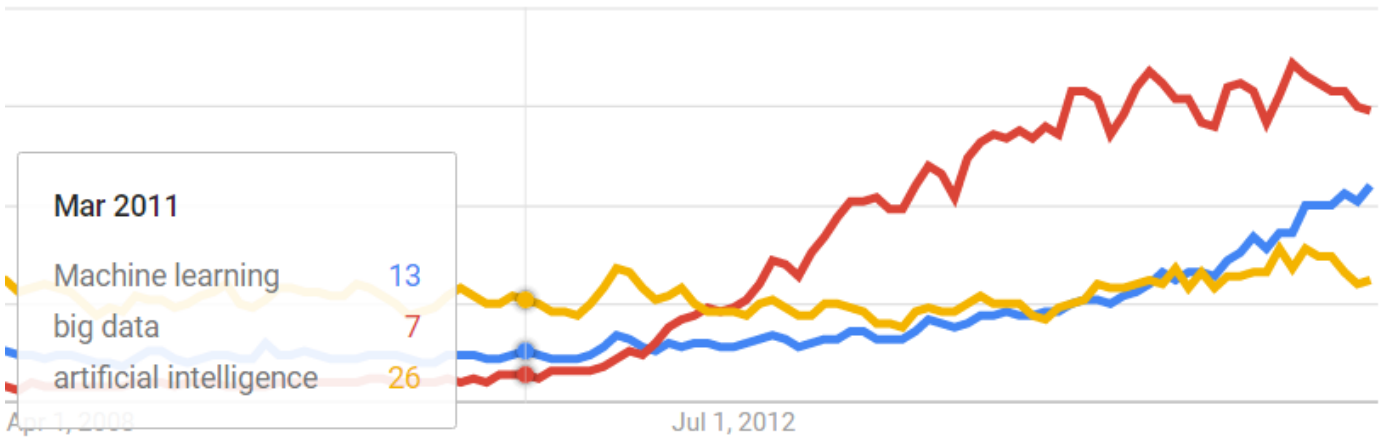
Some Terminology



Outline

Recent Highlights

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"girl in pink dress is jumping in air."

"black and white dog jumps over bar."

Recent Highlights

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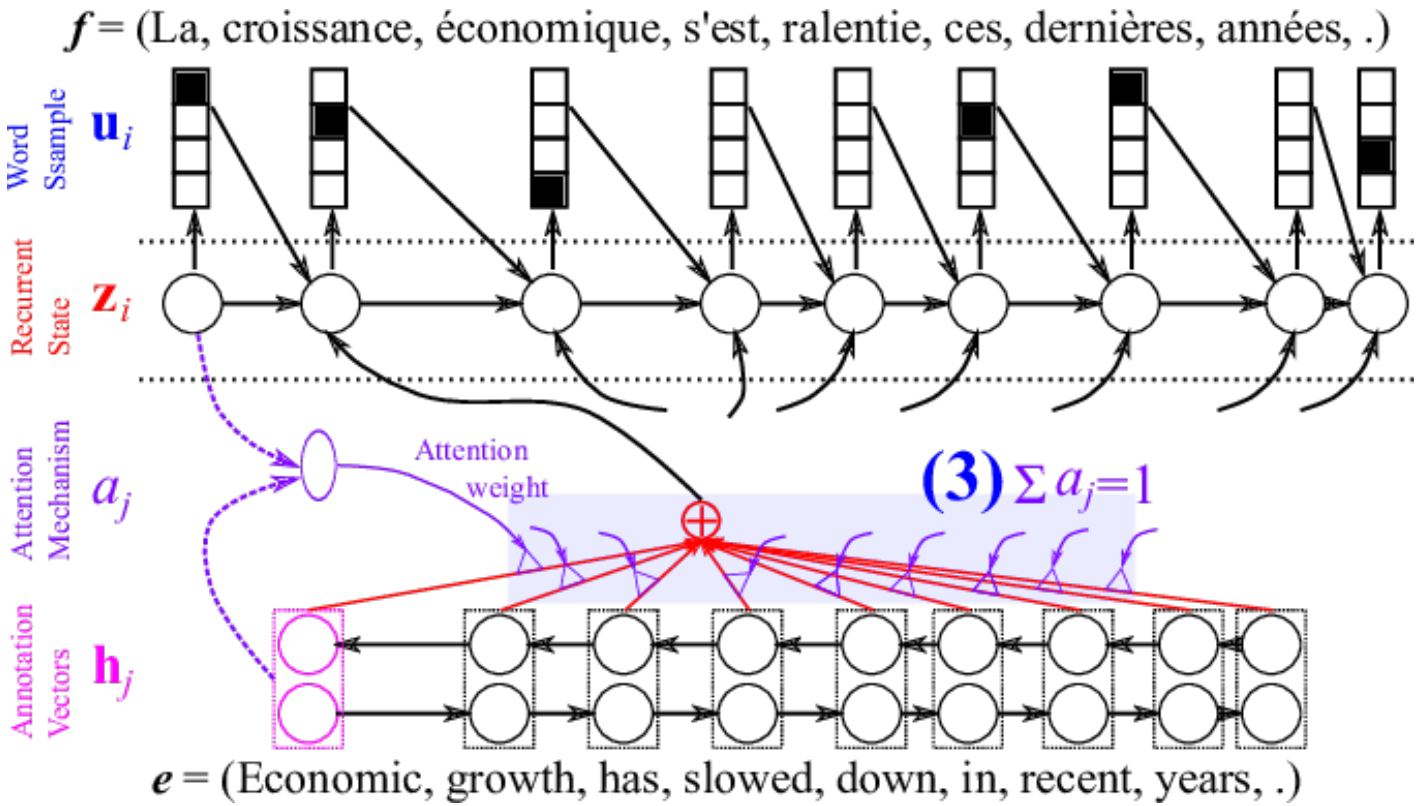

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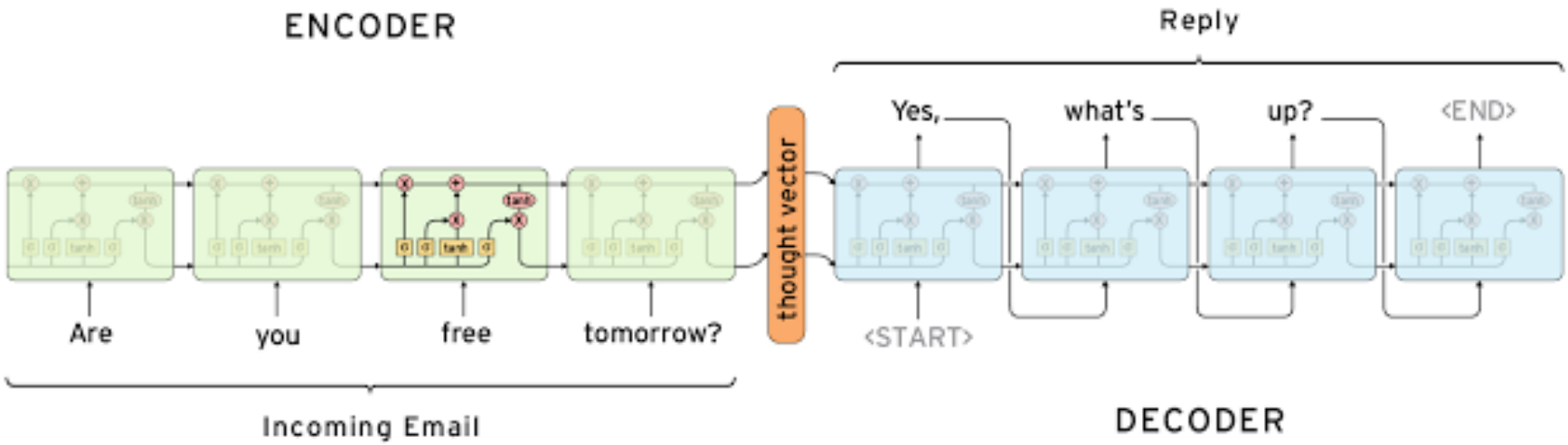

Other Examples

- Speech Recognition

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- Decision Support Systems in Healthcare

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- Predicting Epidemics From Social Media

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- Predicting Epidemics From Social Media
- Targeted Advertising

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- De-anonymization, Fraud Detection, Criminal Identification

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Accuracies tend to increase with more data.

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YOU ARE THE TEACHER!

But, How Do These Work?

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No Free Lunch Theorem

There is always a trade-off

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- Complexity **vs.** Interpretability & Transparency

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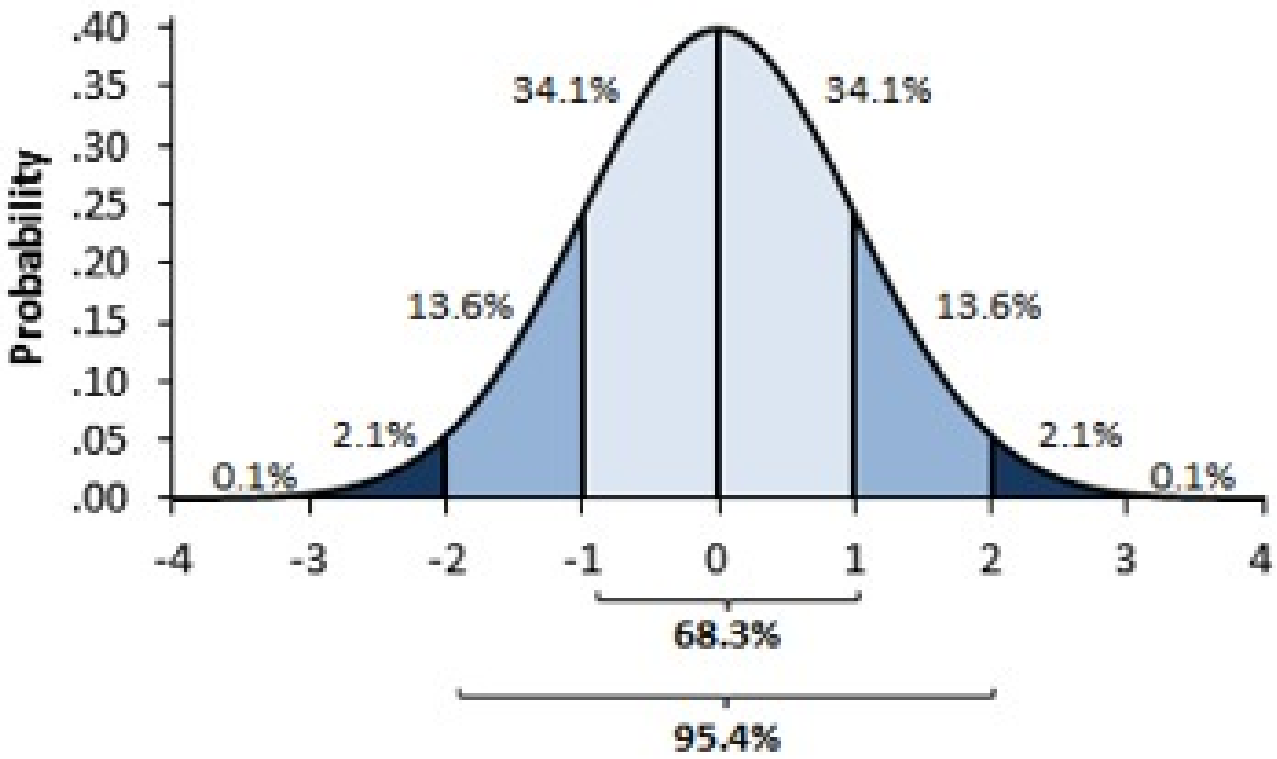

Normal Distribution

- Velocity of Molecules in a Gas

[1] Huxley, Julian S. (1932). Problems of Relative Growth.

[2] Oosterbaan, Roland J. (1994). "Chapter 6: Frequency and Regression Analysis of Hydrologic Data". In Ritzema, Henk P. Drainage Principles and Applications

[3] Andersen, Torben G., et al. (2001) "The distribution of realized stock return volatility." Journal of financial economics 61.1

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Why? $\Longrightarrow$ Central Limit Theorem

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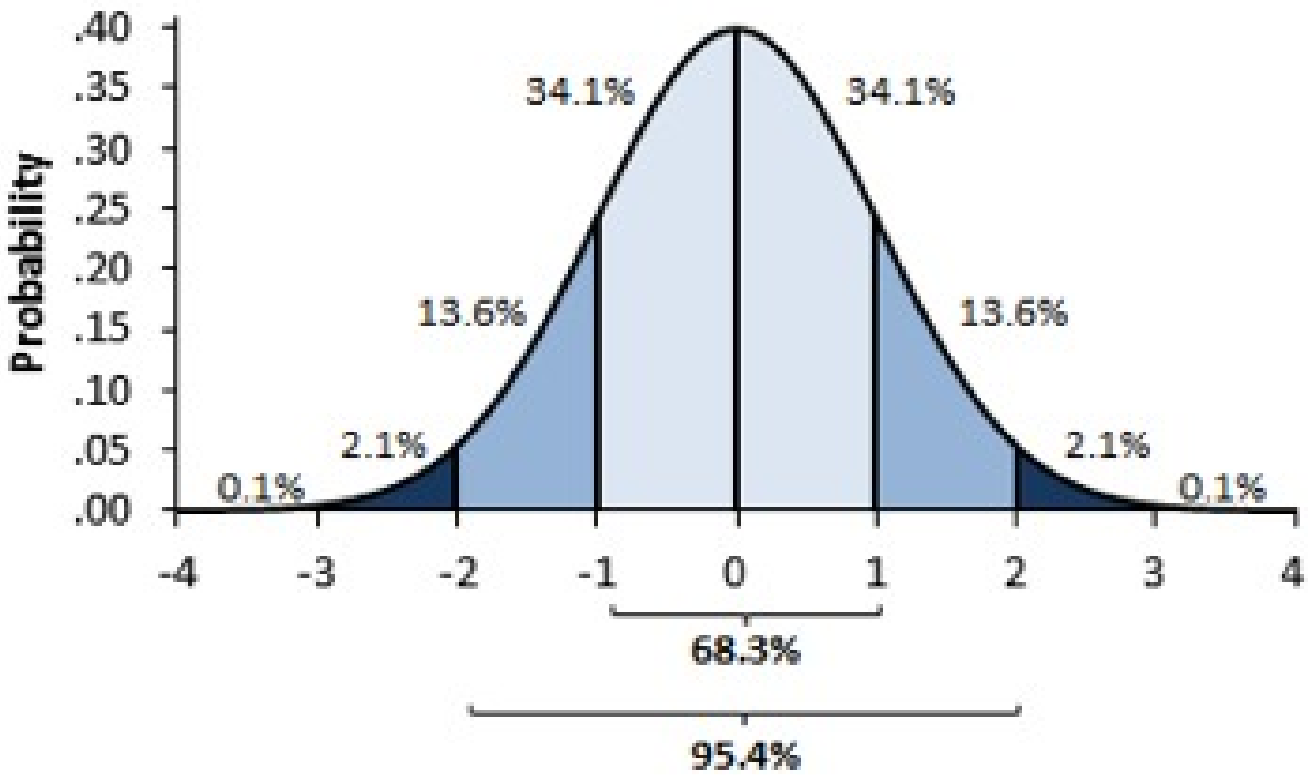
Inevitable Nature of Things



There will be outliers, anomalies and under-represented groups/subsets!

Outline

Consequences

Supervised Algorithms

Consequences

Supervised Algorithms

+

Biased Data

Consequences

Supervised Algorithms

+

Biased Data

=

Biased Algorithms

Ugly Results

If the training data reflect existing social biases against a minority, the algorithm is likely to incorporate these biases.

[4] http://www.independent.co.uk/life-style/gadgets-and-tech/news/googles-algorithm-shows-prestigious-job-ads-to-men-but-not-to-women-10372166.html

[5] http://www.huffingtonpost.com/2015/04/10/google-image-gender-bias_n_7036414.html

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Google image search in USA for *"CEO"* produced 11 % women, even though 27 % of United States chief executives are women.[5]

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Consider a loan application from a bank. Numerous attributes can be an input to a ML algorithm:

- Age
- Field of Work
- Income
- Gender
- Marital Status
- Residence District
- Number of Children
- Transaction History
- Race
- ...

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Biases can be transferred through correlated attributes!

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Discrimination and Privacy-aware ML

Bias-free machine learning research should be encouraged.

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Transparent Design

Is the decision explainable enough?

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Which attributes (features) have been used?

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Importance of attributes inferred by the algorithm?

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Accuracies on different subgroups, false positive & true negative rates.

Box Is Getting Blacker

Black-box models (e.g. neural networks) are extremely popular!

"If it works, I don't care why!" approach.

Conclusion

MyData is important:

The fuel of ML algorithms!

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Increased awareness on interaction of MyData & algorithmic decision making systems is important:

Promotes openness, transparency and bias-free ML approaches!


THANK YOU