Motivation and Basics

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Weekly Objectives

- Motivate the study on
 - Machine learning, AI, Datamining....
 - Why? What?
 - Overview of the field
- Short questions and answers on a story
 - What consists of machine learning?
 - MLE
 - MAP
- Some basics
 - Probability
 - Distribution
 - And some rules...

MOTIVATION

Keywords

- Many floating keywords
 - Data-mining, Knowledge discovery, Machine Learning, Artificial Intelligence...
- Comes from territory, perspectives, types of problems, researchers, etc
- We are going to focus on substance, not labeling.
- I am just going to call it "Machine Learning"

AI in CS You can call it whatever you want **Statistics** Database in Efficien ARTIFICIAL INTELLIGENCE squire Sequentia Constraints Categorical Management Industrial Engineering KAIST Copyright © 20 10 by n-chur woo... astrial and systems Engineering, KAIST

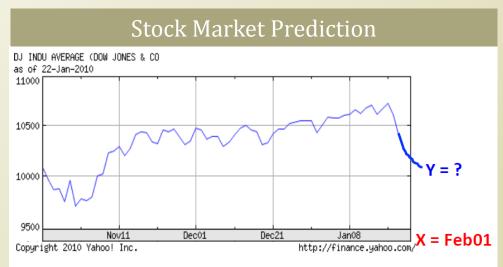
Abundance of Data

Image Data Data are being collect Network Data rywhere Text Data New Hork Dd-m 아고라 **Lwitter** UNITED STATES POSTAL SERVICE 10K Rep. Time Series Data

Examples of Machine Learning Applications

Machine Learning is everywhere...











Spam Filtering and more



Table 2 Detailed evaluation results of SVMs ith each representation scheme and varying training-set sizes. Macro-averaged MAE scores are provided with p-values, indicating the statistical significances of performance improvement over that of BF (using basic features alone). Numbers in bold fond indicate the best method for each fixed training-set size. One star indicates the p-values in (0.01, 0.05]; two stars indicate the p-values equal or less than 1%.

	BF	BF+NC		BF+SI		BF+SIP		BF+SI+NC		BF+SI+NC+SIP	
# of tr	MAE	MAE	p-value	MAE	p-value	MAE	p-value	MAE	p-value	MAE	p-value
10	0.9666	0.9063	* 0.0382	0.8837	* 0.0106	0.8968	* 0.0311	0.9112	* 0.0211	0.8827	** 0.0087
20	0.9720	0.8969	0.0506	0.8596	* 0.0315	0.9095	* 0.0435	0.9071	0.0558	0.8659	* 0.0235

SVM?

- Spam filter
- More?
 - Importance vs. Urgency
- How to predict an important email?
 - Social networks
 - Contents
- Shinjae Yoo, Yiming Yang, Frank Lin, and Il-Chul Moon, Mining Social Networks for Personalized Email Prioritization, ACM SIGKDD Conference, Paris, France, Jun, 28, 2009

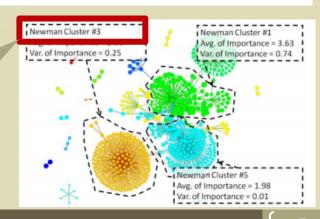
Features

Clusters?
Is this a
machine
learning
technique?

5.3 Features

The basic features are the tokens in the sections of from, to, cc, title, and body text in email messages. Let us use a v-dimensional

is the vocabulary size. We call it the basic feature (BF) sub-vector.



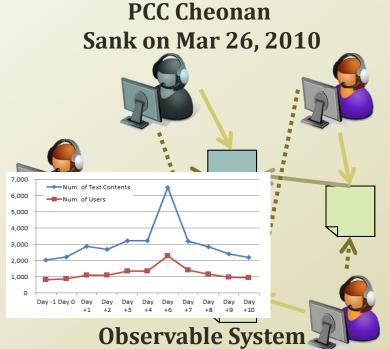
II-Chul Moon, Alice H. Oh, and Kathleen M. Carley, *Analyzing Social Media in Escalating Crisis Situations*, IEEE Conference on Intelligence and Security Informatics (ISI 2011), pp. 71-76, Beijing, China, Jul 10-12, 2011

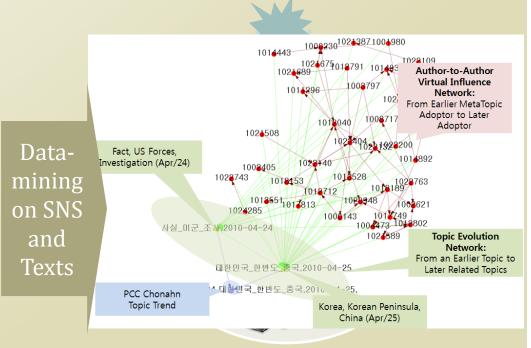
Opinion Mining and more



Finding out consensus of the population

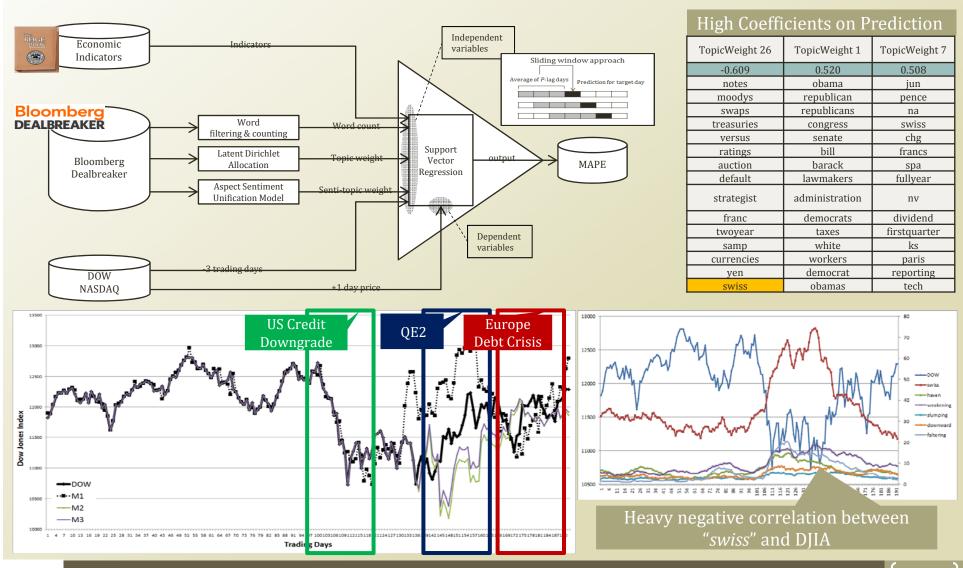
- Mining population's perception of the event
- Mining key opinion buried in a data chunk
- Estimating future polarity of the population
- Strategy to maintain the unity of the population





Implicit System

Stock Market Prediction and more



Types of Machine Learning

Machine Learning

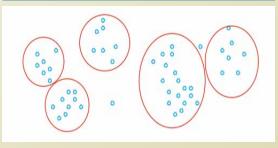
Supervised Learning

You know the true answers of some of instances



Unsupervised Learning

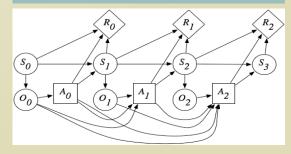
You do not know the true answers of instances



Reinforcement Learning

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You do know the objective, but you do not know how to achieve



• You can

- Machine learning
- Dataset provider
- Machine learning users
- etc

- Various classifications by different professors
 - Purpose, data types, etc
- Other learning classifications also exist

Supervised Learning

- You know the true value, and you can provide examples of the true value.
- Cases, such as
 - Spam filtering
 - Automatic grading
 - Automatic categorization
- Classification or Regression of
 - Hit or Miss: Something has either disease or not.
 - Ranking: Someone received either A+, B, C, or F.
 - Types: An article is either positive or negative.
 - Value prediction: The price of this artifact is X.
- Methodologies
 - Classification: estimating a discrete dependent value from observations
 - Regression: estimating a (continuous) dependent value from observations

Supervised Learning

You know the true answers of some of instances



Unsupervised Learning

- You don't know the true value, and you cannot provide examples of the true value.
- Cases, such as
 - Discovering clusters
 - Discovering latent factors
 - Discovering graph structures
- Clustering or filtering or completing of
 - Finding the representative topic words from text data
 - Finding the latent image from facial data
 - Completing the incomplete matrix of product-review scores
 - Filtering the noise from the trajectory data
- Methodologies
 - Clustering: estimating sets and affiliations of instances to the sets
 - Filtering: estimating underlying and fundamental signals from the mixture of signals and noises

Unsupervised Learning

You do not know the true answers of instances

