UVA CS 4501: Machine Learning

Lecture 9: Supervised Classification

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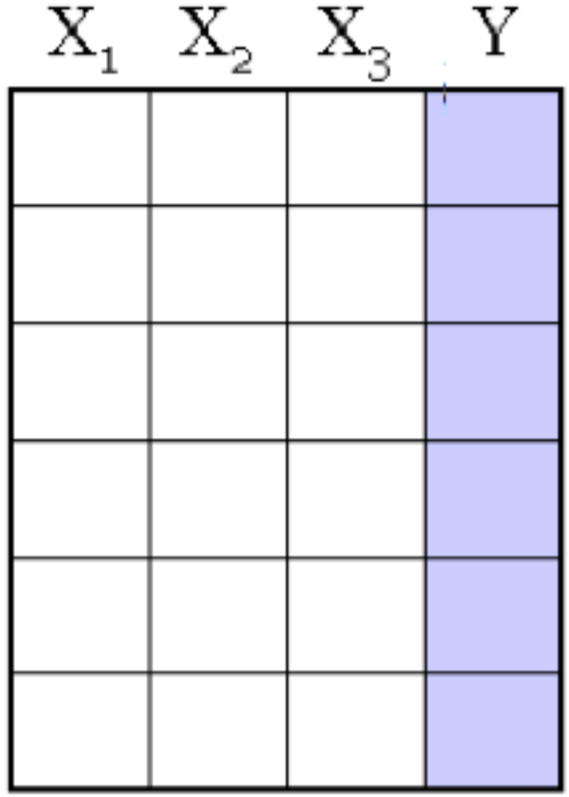
Where are we ? ➔ Five major sections of this course

- ❑ ~~Regression (supervised)~~
- ❑ Classification (supervised)
- ❑ Unsupervised models
- ❑ Learning theory
- ❑ Graphical models

Today ➔
(Intro to Supervised Classification)

- ❑ Applications and Variants
- ❑ Roadmap of section
- ❑ Evaluating Metrics



A Dataset for classification

$$f : X \longrightarrow Y$$

Output Class: categorical variable

- **Data**/*points/instances/examples/samples/records*: [rows]
- **Features**/*attributes/dimensions/independent variables/covariates/predictors/regressors*: [columns, except the last]
- **Target**/*outcome/response/label/dependent variable*: special column to be predicted [last column]

Notation

- Inputs
  - X, X_j (jth element of vector X) : random variables written in capital letter
  - p #inputs, N #observations
  - $\mathbf{X}$: matrix written in bold capital
  - Vectors are assumed to be column vectors
  - Discrete inputs often described by characteristic vector (dummy variables)

- Outputs
  - quantitative Y
  - qualitative C (for categorical)

- Observed variables written in lower case
  - The i-th observed value of X is x_i and can be a scalar or a vector

Many Variants w.r.t. Y

- Binary Classification
- Multi-class Classification
- Hierarchical Classification
- Multi-label Classification
- Structured Predictions
- ……

Binary: Application I: Text Review-based Sentiment Classification

x

I believe that this book is not at all helpful since it does not explain thoroughly the material . it just provides the reader with tables and calculations that sometimes are not easily understood …

Input X : e.g. a piece of English text

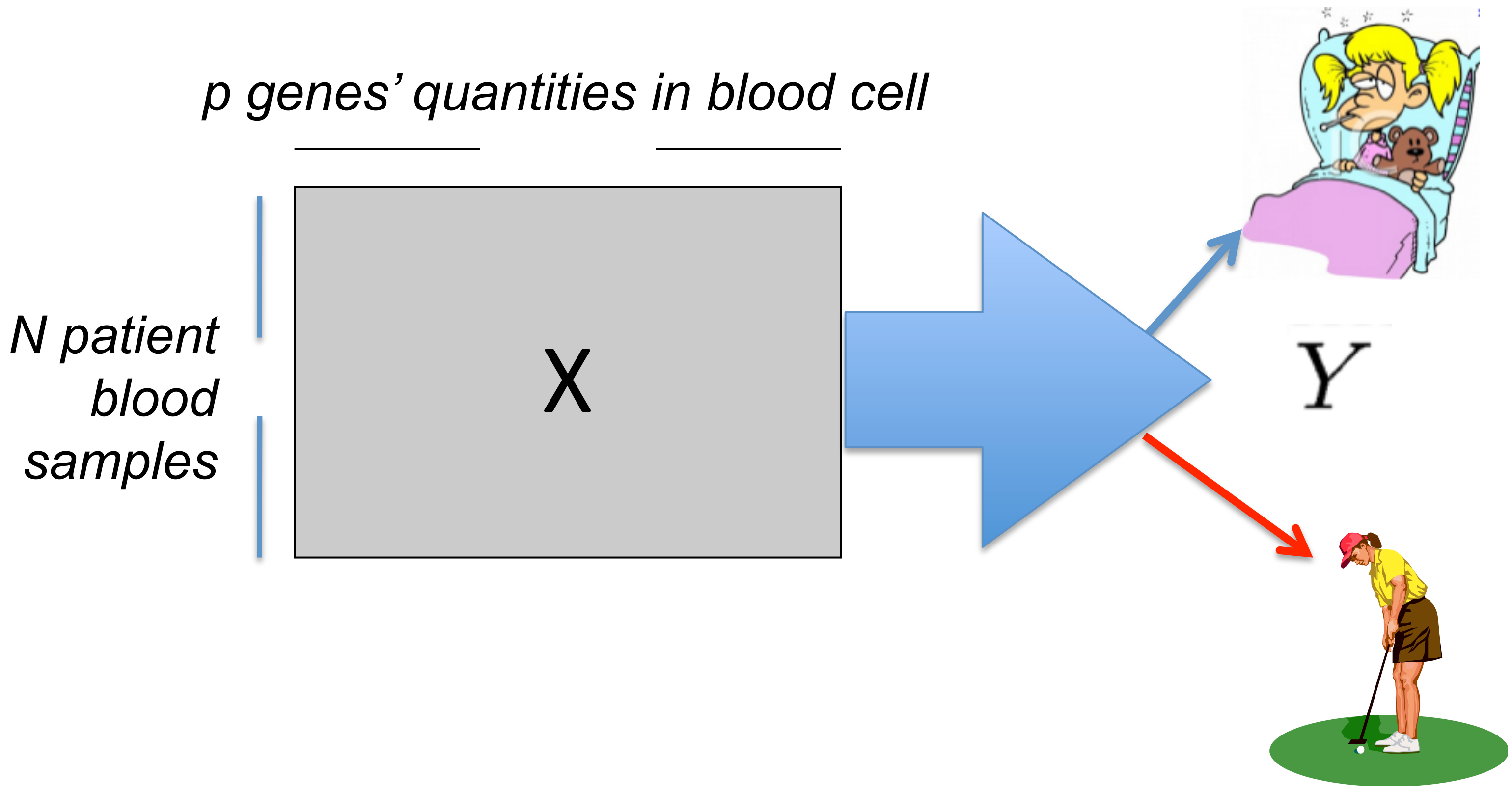
→

y

-1

Output Y: {1 / Yes , -1 / No }
e.g. Is this a positive product review ?

Binary: Application II: **Cancer Classification using gene expression**



Many Variants w.r.t. Y

- Binary Classification
- Multi-class Classification
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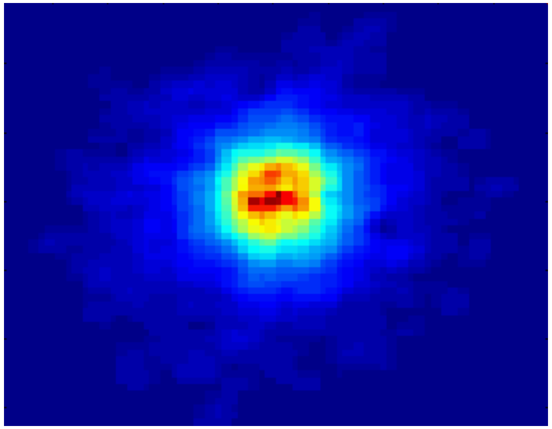
- ……

Multi-Class: Application III: Classifying Galaxies

Courtesy: http://aps.umn.edu

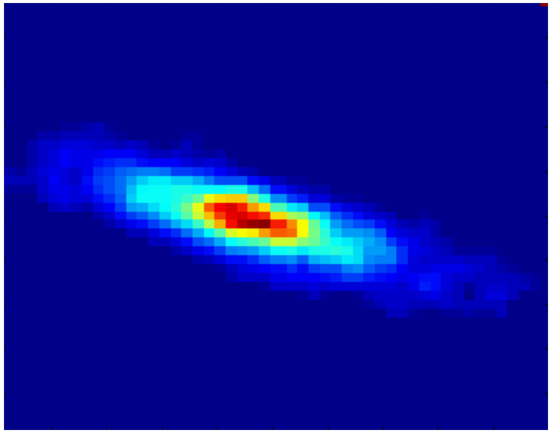
Early



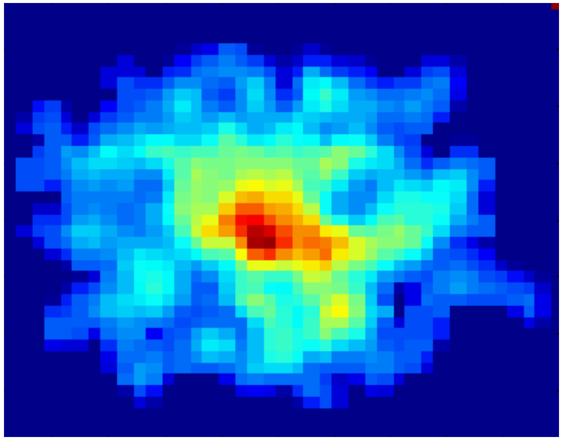
Class:
- Stages of Formation

Attributes:
- Image features,
- Characteristics of light waves received, etc.

Intermediate



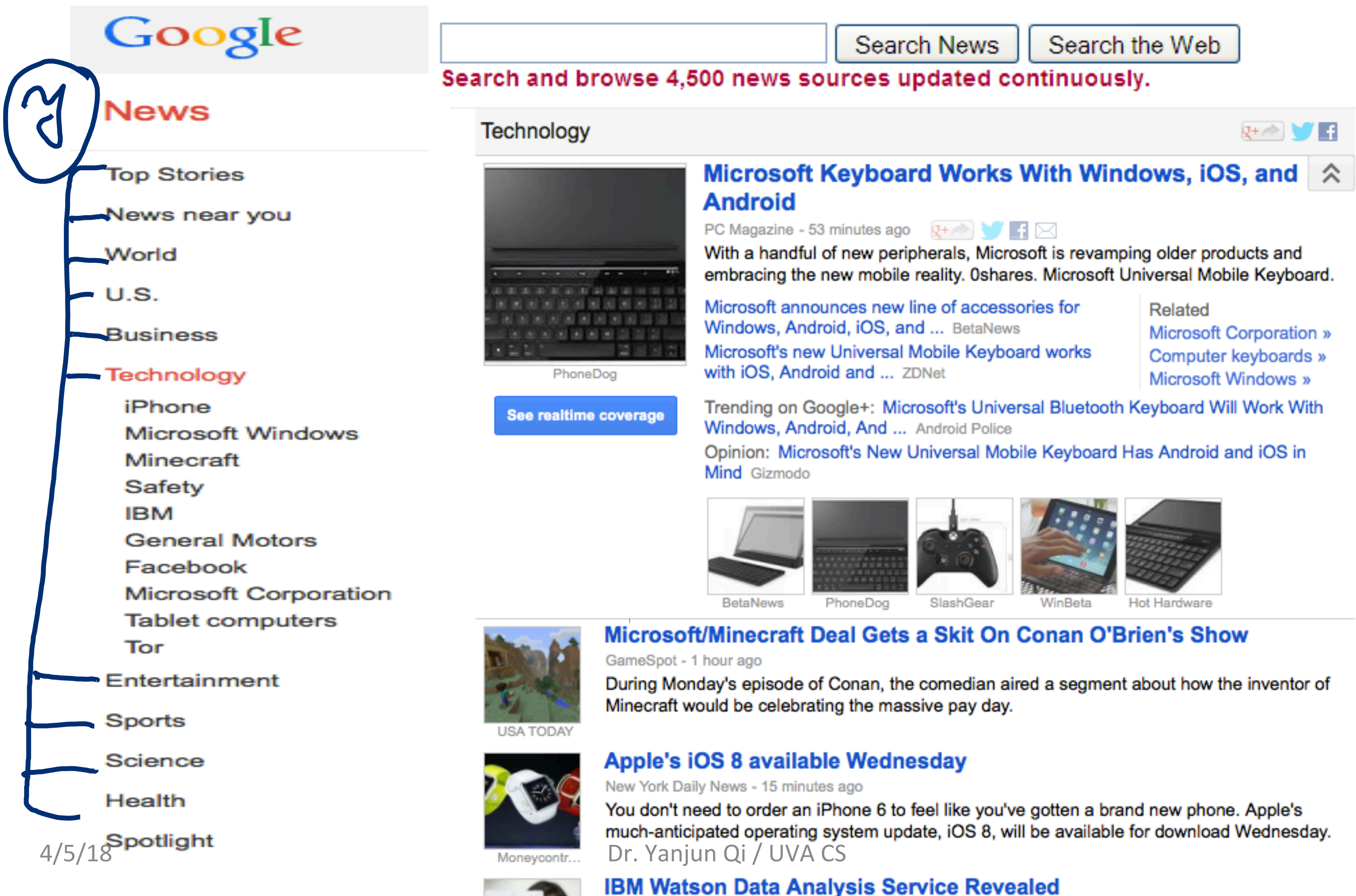
Late



Data Size:
- 72 million stars, 20 million galaxies
- Object Catalog: 9 GB
- Image Database: 150 GB

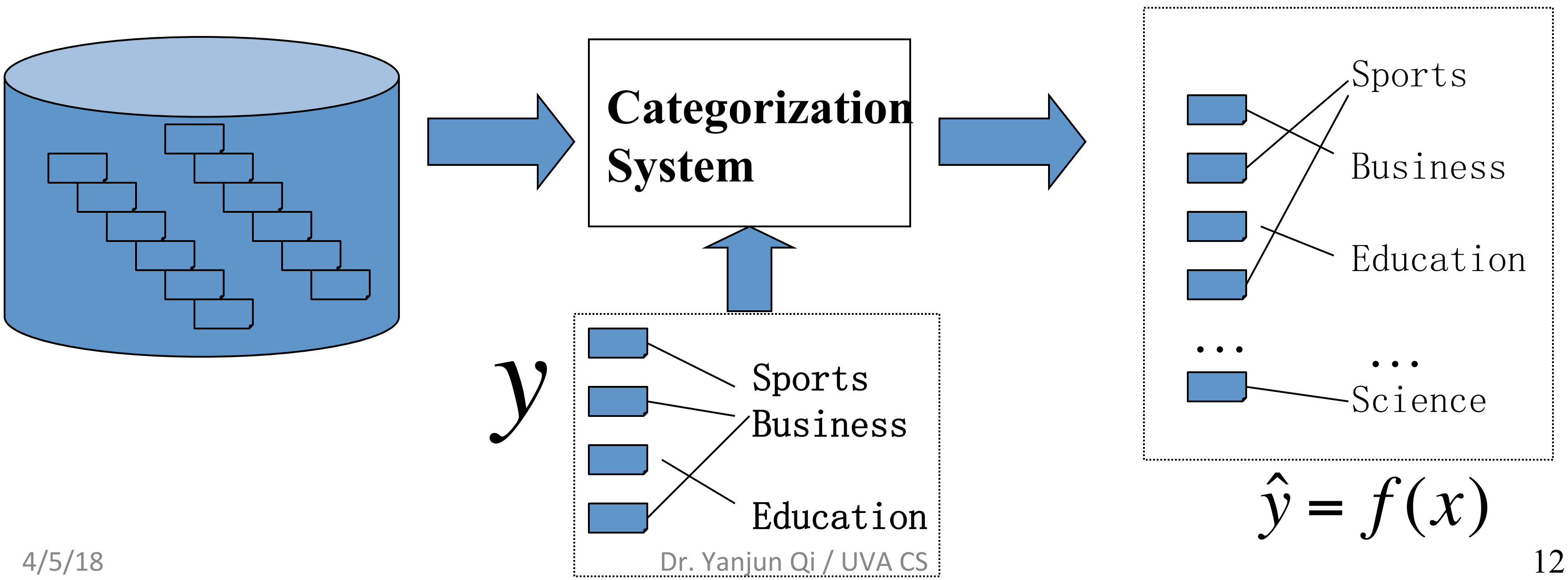
From [Berry & Linoff] Data Mining Techniques, 1997

Hierarchical: Application IV: Text Categorization, e.g. *Google News*



Text Categorization

- Pre-given categories and labeled document examples (Categories may form hierarchy)
- Classify new documents
- A standard supervised learning problem



Examples of Text Categorization

- News article classification
- Meta-data annotation
- Automatic Email sorting
- Web page classification
- ……

Text Document Representation (LATER)

[word]

- Each document becomes a `term' vector,
  - each term is an (attribute) of the vector,
  - the value of each describes the number of times the corresponding term occurs in the document.

Bag of 'words'

	w_1 team	w_2 coach	pla y	ball	score	game	wi n	lost	timeout	w_0 season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

Many Variants w.r.t. Y

- Binary Classification
- Multi-class Classification
- Hierarchical Classification
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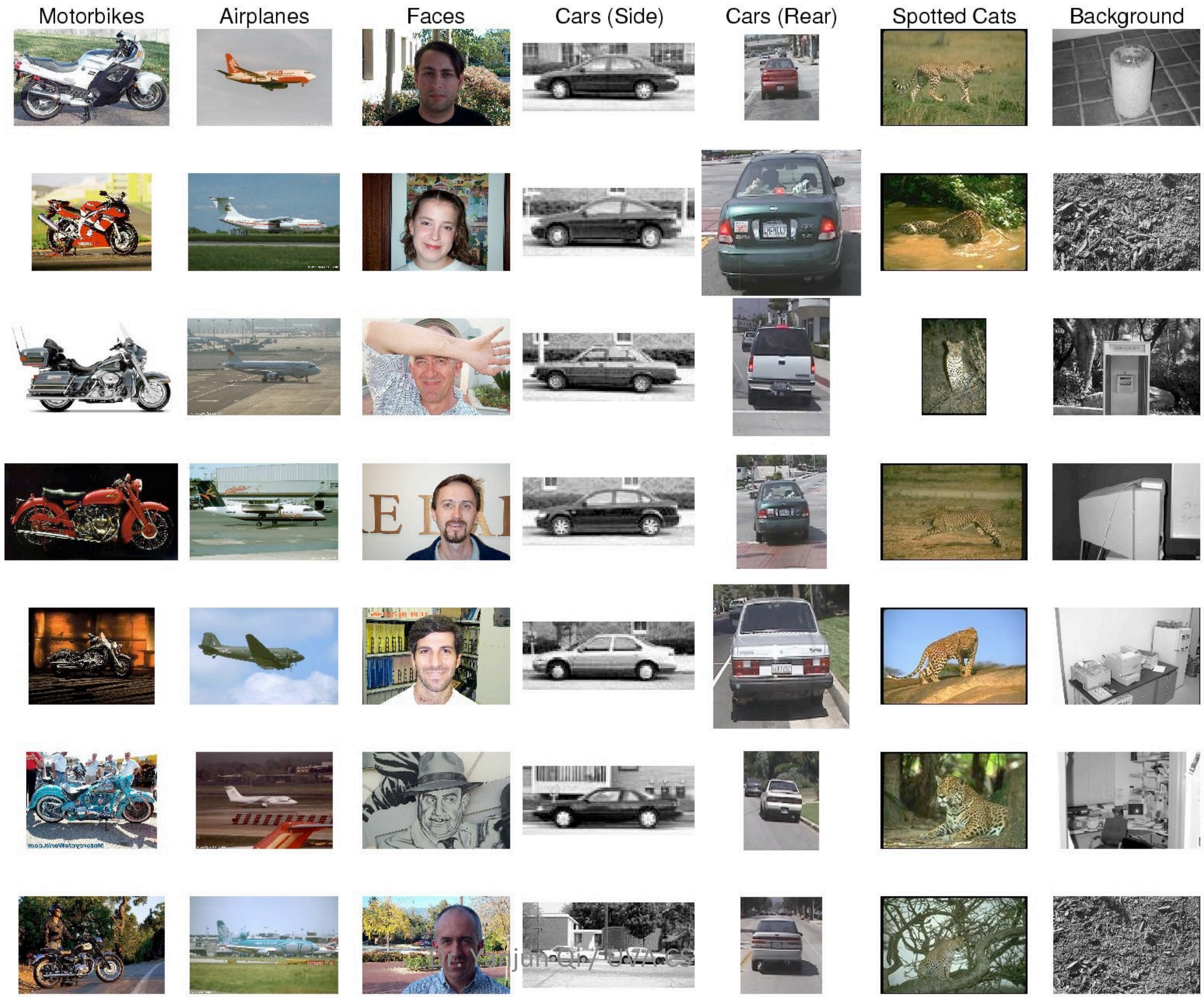
- Structured Predictions
- ……

Multi-Labels: Application V: – Objective recognition / Image Labeling (Label Images into predefined word labels)



When not using Deep Learning: Image Representation for – Objective recognition

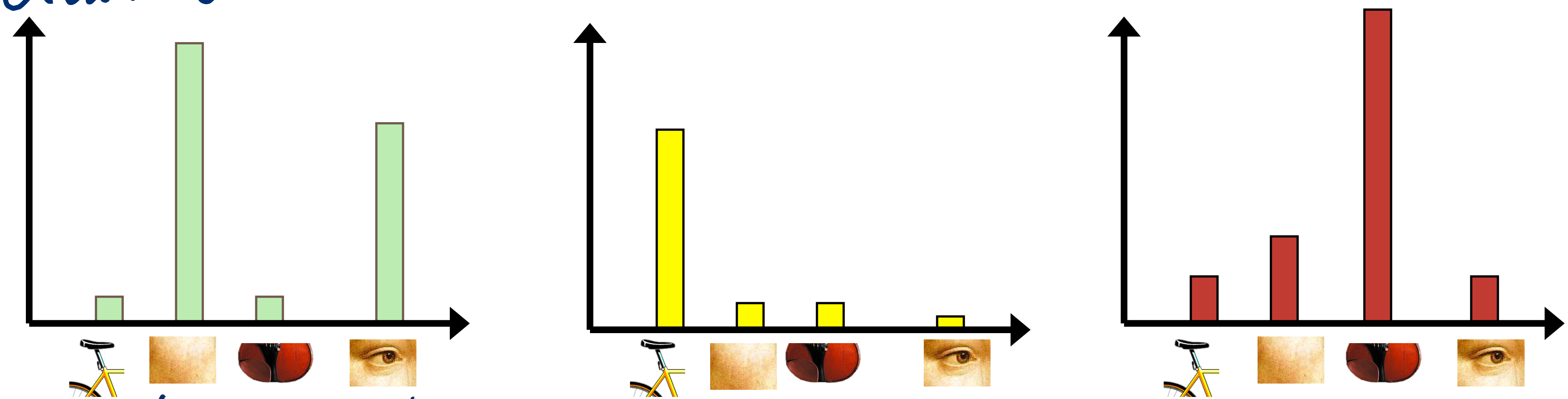
- Image representation → bag of "visual words"

visual

Object → Bag of 'words'

- An object image: histogram of visual vocabulary – a numerical vector of D dimensions.

Occurrence

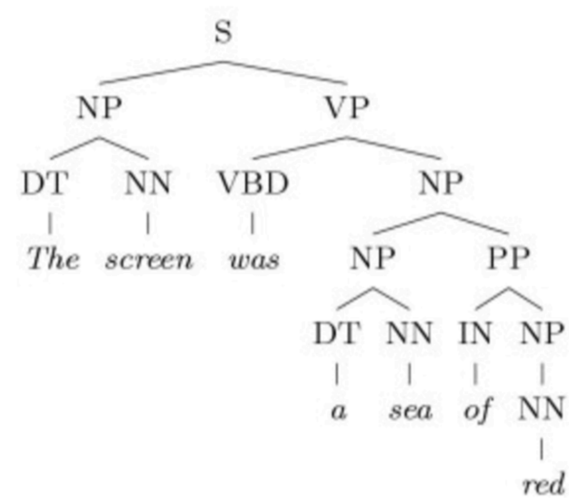


w_1 w_2 w_3.. w_n

Structured Output: Application VI: – Natural Language Parsing

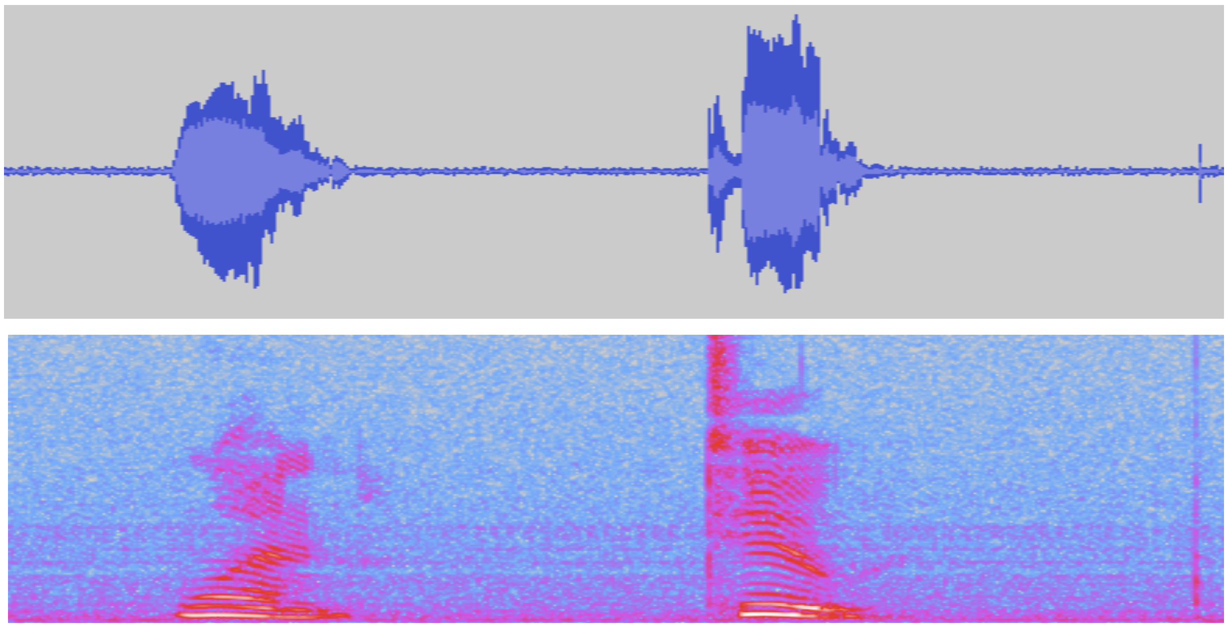
The screen was a sea of red

Language Parsing



From Vicente UVA

Structured Output: Application VII: – Audio Classification



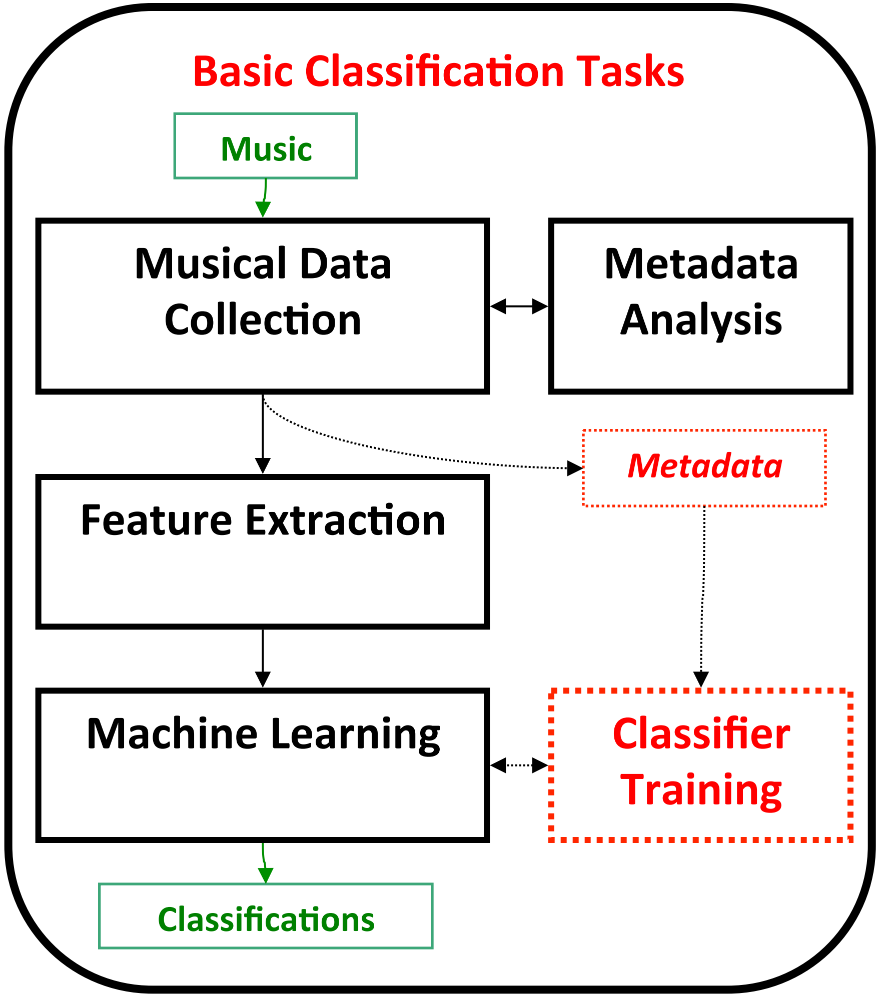
- Real-life applications:
  – Customer service phone routing
  – Voice recognition software

Music Information Retrieval Systems e.g., Automatic Music Classification

- To classify music in various ways
  - Genre or style classification
  - Mood classification
  - Performer or composer identification
  - Music recommendation
  - Playlist generation
  - Hit prediction
  - Audio to symbolic transcription
  - etc.
- Such areas often share similar central procedures

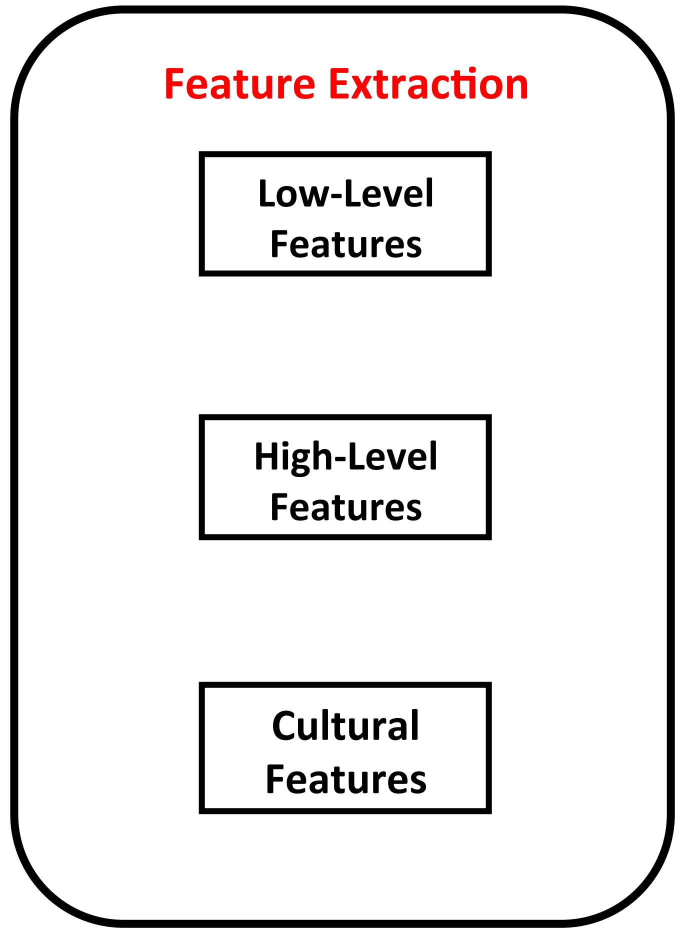
Music Information Retrieval Systems e.g., Automatic Music Classification

- Musical data collection
  - The instances (basic entities) to classify
  - Audio recordings, scores, cultural data, etc.
- Feature extraction
  - Features represent characteristic information about instances
  - Must provide sufficient information to segment instances among classes (categories)
- Machine learning
  - Algorithms ("classifiers" or "learners") learn to associate feature patterns of instances with their classes



Audio, Types of features

- Low-level
  - Associated with signal processing and basic auditory perception
  - e.g. spectral flux or RMS
  - Usually not intuitively musical
- High-level
  - Musical abstractions
  - e.g. meter or pitch class distributions
- Cultural
  - Sociocultural information outside the scope of auditory or musical content
  - e.g. playlist co-occurrence or purchase correlations



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- ❑ Roadmap of section
- ❑ Evaluating Metrics

Three major sections for classification

- We can divide the large variety of classification approaches into roughly three major types

1. Discriminative
   - directly estimate a decision rule/boundary
   - e.g., support vector machine, decision tree, logistic regression,
   - e.g. neural networks (NN), deep NN

2. Generative:
   - build a generative statistical model
   - e.g., Bayesian networks, Naïve Bayes classifier

3. Instance based classifiers
   - Use observation directly (no models)
   - e.g. K nearest neighbors

ICML '06 Proceedings of the 23rd international conference on Machine learning

A study comparing Classifiers

An Empirical Comparison of Supervised Learning Algorithms

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Abstract

A number of supervised learning methods have been introduced in the last decade. Unfortunately, the last comprehensive empirical evaluation of supervised learning was the Statlog Project in the early 90's. We present a large-scale empirical comparison between ten supervised learning methods: SVMs, neural nets, logistic regression, naive bayes, memory-based learning, random forests, decision trees, bagged trees, boosted trees, and boosted stumps. We also examine the effect that calibrating the models via Platt Scaling and Isotonic Regression has on their performance. An important aspect of our study is

This paper presents results of a large-scale empirical comparison of ten supervised learning algorithms using eight performance criteria. We evaluate the performance of SVMs, neural nets, logistic regression, naive bayes, memory-based learning, random forests, decision trees, bagged trees, boosted trees, and boosted stumps on eleven binary classification problems using a variety of performance metrics: accuracy, F-score, Lift, ROC Area, average precision, precision/recall break-even point, squared error, and cross-entropy. For each algorithm we examine common variations, and thoroughly explore the space of parameters. For example, we compare ten decision tree styles, neural nets of many sizes, SVMs with many kernels, etc.

Because some of the performance metrics we examine

A study comparing Classifiers

➔ 11 binary classification datasets

Ratio among label

PROBLEM	#ATTR	TRAIN SIZE	TEST SIZE	%POZ
ADULT	14/104	5000	35222	25%
BACT	11/170	5000	34262	69%
COD	15/60	5000	14000	50%
CALHOUS	9	5000	14640	52%
COV_TYPE	54	5000	25000	36%
HS	200	5000	4366	24%
LETTER.P1	16	5000	14000	3%
LETTER.P2	16	5000	14000	53%
MEDIS	63	5000	8199	11%
MG	124	5000	12807	17%
SLAC	59	5000	25000	50%

A study comparing Classifiers

→ 11 binary classification problems / 8 metrics

ACC ROC

Table 2. Normalized scores for each learning algorithm by metric (average over eleven problems)

MODEL	CAL	ACC	FSC	LFT	ROC	APR	BEP	RMS	MXE	MEAN	OPT-SEL
BST-DT	PLT	.843*	.779	**.939**	**.963**	**.938**	.929*	**.880**	**.896**	**.896**	**.917**
RF	PLT	.872*	.805	.934*	.957	.931	**.930**	.851	.858	.892	.898
BAG-DT	–	.846	.781	.938*	.962*	.937*	.918	.845	.872	.887*	.899
BST-DT	ISO	.826*	.860*	.929*	.952	.921	.925*	.854	.815	.885	.917*
RF	–	**.872**	.790	.934*	.957	.931	**.930**	.829	.830	.884	.890
BAG-DT	PLT	.841	.774	.938*	.962*	.937*	.918	.836	.852	.882	.895
RF	ISO	.861*	**.861**	.923	.946	.910	.925	.836	.776	.880	.895
BAG-DT	ISO	.826	.843*	.933*	.954	.921	.915	.832	.791	.877	.894
SVM	PLT	.824	.760	.895	.938	.898	.913	.831	.836	.862	.880
ANN	–	.803	.762	.910	.936	.892	.899	.811	.821	.854	.885
SVM	ISO	.813	.836*	.892	.925	.882	.911	.814	.744	.852	.882
ANN	PLT	.815	.748	.910	.936	.892	.899	.783	.785	.846	.875
ANN	ISO	.803	.836	.908	.924	.876	.891	.777	.718	.842	.884
BST-DT	–	.834*	.816	**.939**	**.963**	**.938**	.929*	.598	.605	.828	.851
KNN	PLT	.757	.707	.889	.918	.872	.872	.742	.764	.815	.837
KNN	–	.756	.728	.889	.918	.872	.872	.729	.718	.810	.830
KNN	ISO	.755	.758	.882	.907	.854	.869	.738	.706	.809	.844
BST-STMP	PLT	.724	.651	.876	.908	.853	.845	.716	.754	.791	.808
SVM	–	.817	.804	.895	.938	.899	.913	.514	.467	.781	.810
BST-STMP	ISO	.709	.744	.873	.899	.835	.840	.695	.646	.780	.810
BST-STMP	–	.741	.684	.876	.908	.853	.845	.394	.382	.710	.726
DT	ISO	.648	.654	.818	.838	.756	.778	.590	.589	.709	.774

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		actual	
		AP +	− AN
PP	predicted+	TP	FP
PN	predicted−	FN	TN

- (number of) true positive (TP)
- (number of) true negative (TN)
- (number of) false positive (FP)
- (number of) false negative (FN)

(number of) false positive (FP)

eqv. with false alarm, Type I error

(number of) false negative (FN)

eqv. with miss, Type II error

---

sensitivity or true positive rate (TPR)

eqv. with hit rate, recall

$$TPR = \underbrace{TP/P = TP/(TP + FN)}_{\text{Actual Positive}}$$

specificity (SPC) or true negative rate

$$SPC = TN/N = TN/(TN + FP)$$

precision or positive predictive value (PPV)

$$PPV = TP/\underbrace{(TP + FP)}_{\text{PP: predicted positive}}$$

negative predictive value (NPV)

$$NPV = TN/(TN + FN)$$

fall-out or false positive rate (FPR)

$$FPR = FP/\underbrace{N = FP/(FP + TN)}_{\text{Actual Negative}} = 1 - SPC$$

false negative rate (FNR)

$$FNR = FN/(TP + FN) = 1 - TPR$$

false discovery rate (FDR)

$$FDR = FP/(TP + FP) = 1 - PPV$$

---

accuracy (ACC)

$$ACC = (TP + TN)/(TP + FP + FN + TN)$$

F1 score

is the harmonic mean of precision and sensitivity Recall

$$F1 = 2TP/(2TP + FP + FN)$$

From Wiki

$$\text{Accuracy} = \frac{\#\text{Correct Predicted}}{\#\text{all test Examples}}$$

$$= \frac{TP + TN}{TP + FP + TN + FN}$$

$$\left\{ \begin{array}{l} \underline{\text{Pre}}\text{cision\_Pos} = \dfrac{TP}{PP} \\ \underline{\text{Re}}\text{call\_Pos} = \dfrac{TP}{TP+FN} \end{array} \right\}$$

When with Unbalanced Issue (binary case)

- Class imbalance issue $\text{num } \underbrace{AP}_{\text{actual Positive}} << \text{num } \underbrace{AN}_{\text{actual neg}}$
- Balanced accuracy: $= \frac{1}{2}\left(\frac{TP}{PP} + \frac{TN}{PN}\right)$ $PP \to TP+FP$ $PN \to TN+FN$

	actual	
	$+$	$-$
predicted$+$	TP	FP
predicted$-$	FN	TN

Ratio of Positive Class (binary case)

$(1, 99)$
pos neg

If $\frac{\text{Actual P}}{\text{AP} + \text{AN}}$ very small (e.g. $< 1\%$)

$\Rightarrow$ a classifier can predict every example as Neg

$\Rightarrow$ ①

	AP ①	AN 99
predict P	0	0
predict N	1	99

$\Rightarrow$ Accuracy $= \frac{99}{100} = 0.99$

$\Rightarrow$ Balanced Acc =

Bad-neg-classifier

① Balanced Acc $= \frac{1}{2}\left(\frac{TP}{P} + \frac{TN}{N}\right)$

$= \frac{1}{2}\left(\frac{0}{0+\epsilon} + \frac{99}{100}\right) = 0.495$

$[0, 1]$

another classifier

②

	AP	AN
PP	1	0
PN	0	99

Balanced Acc $= \frac{1}{2}\left(\frac{1}{1} + \frac{99}{99}\right) = 1$

$\text{Acc} = \frac{1+99}{1+0+99+0} = 1$

(PosRatio 1/100)

③ Third classifier

	AP	AN
PP+	0	1
PN-	1	99

$$ACC = \frac{99}{101} \approx 99\%$$

$$BACC = \frac{1}{2}\left(\frac{0}{1} + \frac{99}{100}\right) \approx 0.495$$

(Pos Ratio 2/120)

④ Fourth case

	AP	AN
PP+	1	19
PN-	1	99

$$ACC = \frac{100}{120} \approx 83\%$$

$$BACC = \frac{1}{2}\left(\frac{1}{20} + \frac{99}{100}\right) \approx 0.52$$

Today Recap
(Intro to Supervised Classification)

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References

- Big thanks to Prof. Ziv Bar-Joseph and Prof. Eric Xing @ CMU for allowing me to reuse some of his slides
- <u>Elements of Statistical Learning, by Hastie, Tibshirani and Friedman</u>
- Prof. Andrew Moore @ CMU's slides
- Tutorial slides from Dr. Tie-Yan Liu, MSR Asia