### Machine Learning

Intro to Al Bert Huang Virginia Tech

# Machine Learning

- Learning: improving with experience at some task
  - Improve over **task**
  - with respect to some **performance measure**
  - based on some experience
- Writing computer programs that write computer programs

Learning definition by Tom Mitchell



- Three machine learning stories/cautionary tales
- Deep learning definition
- Types of machine learning
- Best practices

#### Outline

## Machine Learning Story 1 Face Detection & Recognition







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Find photos by what's in them

Looking for that photo of your pup? Just tap "dog" or the place you took it to find it faster.



#### What Does a Human Face Look Like?

















Apple II image from wikipedia.com. Eyes added digitally.



Apple II image from wikipedia.com. Eyes added digitally.



if pixel153 > 128 & pixel154 > 128 & pixel155 > 128 & pixel156 < 64 & sqrt(pixel157) < 82 & log(pixel1132 \* pixel1133) > 1 .... then image is a face\*

\* (not a real face recognition program)

Apple II image from wikipedia.com. Eyes added digitally.





































## Machine Learning Story 2 Recommender Systems



#### Browse Genre Stations

0



#### People You May Know see all



Jim M Add as Friend



Erin Elizabeth K Add as Friend



Josh S Add as Friend

#### **Recommended for You**







Figure from Koren, Bell, Volinksy, IEEE Computer, 2009





# Applications of Recommendation

- Music
- Medicine
- Jobs

- Movies
- Books

Education

# Applications of Recommendation

- Movies
- Books
- Music
- Medicine
- Education
- Jobs





## Machine Learning Story 3 Housing Markets

# ASA Excellence in Statistical Reporting Award The formula that killed Wall Street

Wall Street in the mid-1980s turned to the quants – brainy financial engineers – to invent new ways to boost profits. They and their managers, though laziness and greed, built a huge financial bubble on foundations that they did not understand. It was a recipe for disaster. The journalist **Felix Salmon** won the American Statistical Association's Excellence in Statistical Reporting Award for 2010. We reprint his article, first published as the cover story of *Wired* magazine, because it brilliantly conveys complex statistical concepts

A formula in statistics, misunderstood and misused, has devastated the qlobal economy

significance february2012 16

In the years before 2008, it was hardly unth that a math wizard like David X. Li might so earn a Nobel Prize. After all, financial econor even Wall Street quants - have received the in economics before, and Li's work on measur has had more impact, more quickly, than p Nobel Prize-winning contributions to the field though, as dazed bankers, politicians, regulate investors survey the wreckage of the biggest fi meltdown since the Great Depression, Li is p thankful he still has a job in finance at all. N his achievement should be dismissed. He too toriously tough nut – determining correlation, seemingly disparate events are related - and

![](_page_20_Figure_3.jpeg)

#### $\Pr[\mathsf{T}_{A} < 1, \mathsf{T}_{B} < 1] = \phi_{2}(\phi^{-1}(\mathsf{F}_{A}(1)), \phi^{-1}(\mathsf{F}_{B}(1)), \gamma)$

The formula that killed so many pension plans: David X. Li's Gaussian copula, as first published in 2000. Investors exploited it as a quick – and fatally flawed – way to assess risk.

#### **Probability**

Specifically, this is a joint default probability – the likelihood that any two members of the pool (A and B) will both default. It's what investors are looking for, and the rest of the formula provides the answer.

#### Copula

This couples (hence the Latinate term copula) the individual probabilities associated with A and B to come up with a single number. Errors here massively increase the risk of the whole equation blowing up.

#### Survival times

The amount of time between now and when A and B can be expected to default. Li took the idea from a concept in actuarial science that charts what happens to someone's life expectancy when their spouse dies.

#### **Distribution functions**

The probabilities of how long A and B are likely to survive. Since these are not certainties, they can be dangerous: Small miscalculations may leave you facing much more risk than the formula indicates.

#### Equality

A dangerously precise concept, since it leaves no room for error. Clean equations help both quants and their managers forget that the real world contains a surprising amount of uncertainty, fuzziness, and precariousness.

#### Gamma

The all-powerful correlation parameter, which reduces correlation to a single constant - something that should be highly improbable, if not impossible. This is the magic number that made Li's copula function irresistible.

# Machine Learning Stories

- Face recognition
- Recommender systems
- Finance

# What is deep learning?

raw image input image preprocessing edge detection object detection object identification

raw image input learnable component (neural network) another neural network another neural network object identification

![](_page_23_Picture_3.jpeg)

- process from raw input to raw output
  - training/designing each component on its own

## Deep Learning

### Using machine learning to simultaneously train every part of the

Considered "deep" when compared to "shallow" approach of

# Types of Machine Learning

- Types of learning settings
  - Supervised learning
  - Unsupervised learning
- Types of learning algorithms
  - Batch learning
  - Online learning

## Example: Digit Classification

![](_page_26_Picture_1.jpeg)

#### http://ufldl.stanford.edu/housenumbers/

![](_page_26_Picture_3.jpeg)

## Example: Airline Price Prediction

![](_page_27_Figure_1.jpeg)

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<b>9:05p</b> HNI	_ → 1:35p	<b>CLT</b> 10h 30m	1 stop (PHX)		
Show details	S ▼			Economy	
American Airlines					
6:10a CLT	· → 12:22	<b>p HNL</b> 12h 12m	1 stop (DFW)		
<b>9:05p</b> HNI	_ → 1:35p	CLT 10h 30m	1 stop (PHX)		

## Example: Airline Price Prediction

![](_page_28_Figure_1.jpeg)

Sort by: price (low to high) -

\$367 Honolulu Round Trip cheapoair.com/Honolulu-Cheap-Flight

![](_page_28_Figure_8.jpeg)

# Batch Supervised Learning

- Draw data set  $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$  from distribution  $\mathbb{D}$
- Algorithm A learns hypothesis  $h \in H$  from set H of possible hypotheses A(D) = h
- We measure the quality of h as the expected loss:  $E_{(x,y)\in\mathbb{D}} [\ell(y, h(x))]$ 
  - This quantity is known as the **risk**

• E.g., loss could be the Hamming loss  $\ell_{\text{Hamming}}(a, b) = \begin{cases} 0 & \text{if } a = b \\ 1 & 1 \end{cases}$ . otherwise classification

#### Online Supervised Learning • In step **t**, draw data point **x** from distribution $\mathbb{D}$

- Current hypothesis **h** guesses the label of **x**
- Get true label from oracle **O**
- Pay penalty if **h(x)** is wrong (or earn reward if correct)
- - Does not store history

• Learning algorithm updates to new hypothesis based on this experience

# Learning Settings

- Supervised or unsupervised (or semi-supervised, weakly) supervised, transductive...)
- Online or batch (or reinforcement...)
- Classification, regression

(or structured output, clustering, dimensionality reduction...)

#### Best Practices

- Try range of models with different **capacity**
- Split data into training, validation, and testing sets
- Measure performance on evaluation set to tune parameters
- Measure performance on testing set as final check

### Held-out Validation

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## Held-out Validation

0	<b>\</b>				Accuracy on training data	Accuracy on validation data
2 3	3	2	3	Simple	0.91	0.83
4 5	4	4 4	4 5	Medium	0.95	0.88
6	6		5	Complex	0.99	0.79
8	8	8	3 1	Super Complex	1.0	0.54

#### training data

![](_page_34_Figure_3.jpeg)

validation data

![](_page_34_Picture_5.jpeg)

### Summary

- Three machine learning stories
  - One cautionary tale
- Deep learning definition
- Types of machine learning
- Best practices