CSE 151 Intro. to AI: A Statistical Approach

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Course Staff

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Office Hours:  F1-2pm, CSE 4110

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   Songbai Yan
   Shang Liu

Tutor: Shuang Liu

Website:

   http://cseweb.ucsd.edu/classes/sp18/cse151-a/
What is Machine Learning?

How to use data to learn to make better predictions

Example 1: Recommendation Systems
What is Machine Learning?

How to use data to learn to make better predictions

Example 2: Spam Detection
What is Machine Learning?

How to use data to learn to make better predictions

Example 3: Link Prediction
What is Machine Learning?

How to use data to learn to make better predictions
Algorithm behavior changes based on data

This class: some basic machine learning methods
Two Types of Machine Learning

Supervised Learning
Given examples of data and their labels, predict labels of new (unseen) data

Unsupervised Learning
Given data, build a model or cluster

There are other types, but we won’t get to it in this class
Supervised Learning

Classification:
Given labeled data:

\[(x_i, \ y_i) \quad i=1,\ldots,n\]

where \(y\) is discrete, find a rule to predict \(y\) values for unseen \(x\)
Typical Classification Algorithm

Set of input examples $(x_i, y_i)$

Classification Algorithm

Prediction Rule

New example $x$

Label $y$
Typical Classification Algorithm

Set of input examples \((x_i, y_i)\)

Classification Algorithm

Prediction Rule

Test Data

New example \(x\)

Label \(y\)

Training and test data must be separate!
Typical Classification Algorithm

Set of input examples \((x_i, y_i)\)

Classification Algorithm

Prediction Rule

New example \(x\)

Label \(y\)

Test Data

Performance Measure:
Accuracy (or fraction of correct answers) on test data
Supervised Learning

Classification: Given labeled data \((x_i, y_i)\)
where \(y\) is discrete, predict \(y\) values for unseen \(x\)

Example 1: Predict if a new patient has flu or not, based on existing patient data

What is \(x\) and \(y\)?
Supervised Learning

Classification: Given labeled data \((x_i, y_i)\)
where \(y\) is discrete, predict \(y\) values for unseen \(x\)

Example 1: Predict if a patient has flu or not

<table>
<thead>
<tr>
<th>Fever</th>
<th>Cold</th>
<th>Temperature</th>
<th>Flu?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>No</td>
<td>99F</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Features: Properties of patient
Label: Flu/No flu

\[ x = \begin{bmatrix} 1 \\ 0 \\ 99 \end{bmatrix}, \quad y = + \]

A binary (two-label) classification problem
Supervised Learning

Classification: Given labeled data \((x_i, y_i)\)
where \(y\) is discrete, predict \(y\) values for unseen \(x\)

Example 2: Which digit in the image?

A multiclass classification problem
Supervised Learning

Classification: Given labeled data \((x_i, y_i)\) where \(y\) is discrete, predict \(y\) values for unseen \(x\).

Example 2: Which digit in the image?

Label: 0, 1,..., 9

What are the features?
Option: vector of pixel colors

Image

\[
\begin{array}{cccccc}
0 & 1 & 2 & 3 & 4 \\
5 & 6 & 7 & 8 & 9 \\
\end{array}
\]

\[
\begin{array}{cccccc}
& & & & & \\
& & & & & \\
& & & & & \\
\end{array}
\]

\[
0 \ 0 \ 0 \ 1 \ 0 \ 1 \ 0 \ 1 \ ...
\]

\(x\) (0 for white, 1 for black)
Supervised Learning

Classification: Given labeled data \((x_i, y_i)\) where \(y\) is discrete, predict \(y\) values for unseen \(x\)

Example 2: Which digit in the image?

0 1 2 3 4
5 6 7 8 9

Label: 0, 1, ..., 9

What are the features?
Option: vector of pixel colors

There are other options too

Lesson: Choosing features is non-trivial in real applications
Supervised Learning

Classification: Given labeled data \((x_i, y_i)\) where \(y\) is discrete, predict \(y\) values for unseen \(x\)

Example 3: Spam or not?

<table>
<thead>
<tr>
<th>Email 1</th>
<th>Email 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>From: Canadian Pharmacy</td>
<td>From: Yuncong Chen</td>
</tr>
<tr>
<td>Subject: Offer ends now!</td>
<td>Subject: TA meeting</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pharmacy</th>
<th>offer</th>
<th>meeting</th>
<th>TA</th>
<th>Spam?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Email 1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Email 2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Label: 0 (not spam), 1 (spam) Features: Words in the email
Supervised Learning

Regression:
Given data:
\[(x_i, y_i) \quad i=1,\ldots,n\]

where \( y \) is continuous, design a rule to predict \( y \) values for unseen \( x \)
Supervised Learning

**Regression:** Given data \((x_i, y_i)\)
where \(y\) is **continuous**, predict \(y\) values for unseen \(x\)

**Example 1:** Predict house price from properties of house

<table>
<thead>
<tr>
<th>Bedrooms</th>
<th>Bathrooms</th>
<th>Area</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>2</td>
<td>2000</td>
<td>600K</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1200</td>
<td>400K</td>
</tr>
</tbody>
</table>

Independent Variable: Property of house
Dependent variable: Price
Two Types of Machine Learning

Supervised Learning
Given examples of data and their labels, predict labels of new (unseen) data
Examples: Classification, Regression

Unsupervised Learning
Given data, build a model

There are other types, but we won’t get to it in this class
Unsupervised Learning

Clustering
Given a set of input objects, group them to clusters by similarity

Example 1: Cluster videos by people in them
Unsupervised Learning

Clustering
Given a set of input objects, group them to clusters by similarity

Example 2: Cluster documents by topic

Physics
  - Gravity
  - Laws of Motion
  - Electricity

Math
  - Geometry
  - Algebra

Features: Words in the document
Unsupervised Learning

Dimensionality Reduction
Given high dimensional data, find a good low dimensional representation

Example 1: Images

\[
\begin{array}{cccc}
0 & 1 & 2 & 3 \\
4 & 5 & 6 & 7 \\
8 & 9 \\
\end{array}
\]

Number of pixels = 768, so 768-dimensional object
Can we find a lower dimensional representation?
Two Types of Machine Learning

Supervised Learning
Given examples of data and their labels, predict labels of new (unseen) data
Examples: Classification, Regression

Unsupervised Learning
Given data, build a model
Examples: Clustering, Dimension Reduction, learning HMMs

There are other types, but we won’t get to it in this class
Logistics

Instructor: Kamalika Chaudhuri
Email: kamalika@cs.ucsd.edu

Lecture: MWF 11-11:50
Sections (optional): M 2-2:50pm, 3-3:50pm

Website: http://cseweb.ucsd.edu/classes/sp18/cse151-a/
Textbooks:
No textbook for this class

Syllabus:
Classification -- k-NN, Perceptron, Boosting, etc.
Linear Least Squares Regression
Unsupervised learning -- k-means, hierarchical clustering
Prerequisites

Probability: Events, random variables, expectations, joint, conditional and marginal distributions, independence

Linear Algebra: Vector spaces, subspace, matrix inversion, matrix multiplication, linear independence, rank, determinant, bases, orthonormality, solving systems of linear equations

Calculus: Minima, maxima of functions, derivatives, integrals

Programming: Write programs in a language of your choice. No hand-holding provided
Prerequisites

Calibration homework HW0 on class website

Calibration quiz Quiz0 on Fri Apr 13

HW0 covers most (but not all) of the material you need to know as a pre-requisite
Assessment

Homeworks (7): 0%  (for self-study only)
Quiz (7): 50%
Programming Assignments (5): 25%
Final: 25%

We will be using GradeSource
Homeworks

There are seven homeworks, one on each topic

Homeworks are for self-study only
Programming Assignments

There are five programming assignments

Lowest one will be dropped in calculating your grade

You can use any language and any libraries for your programming assignments

If you use external libraries, it is your responsibility to make sure they give you correct answers

Email us a copy of your code with your assignment (instructions later)
Quizzes

There are seven quizzes, one for each HW

Each quiz is 20 mins

If you understand how to do a HW, you should be able to do the corresponding quiz

Lowest one will be dropped in calculating your grade
**Quiz Schedule**

No makeup quizzes except for medical emergencies

<table>
<thead>
<tr>
<th>Quiz #</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>4/13</td>
</tr>
<tr>
<td>1</td>
<td>4/20</td>
</tr>
<tr>
<td>2</td>
<td>4/27</td>
</tr>
<tr>
<td>3</td>
<td>5/11</td>
</tr>
<tr>
<td>4</td>
<td>5/18</td>
</tr>
<tr>
<td>5</td>
<td>6/1</td>
</tr>
<tr>
<td>6</td>
<td>6/8</td>
</tr>
</tbody>
</table>
Questions

Message board for this class on Piazza
Please post your questions on the message board!
Typical Classification Algorithm

Set of input examples \((x_i, y_i)\)

Classification Algorithm

Test Data
New example \(x\)

Prediction Rule

Label \(y\)

Training and test data must be separate!
Generative Classification

Goal: Classify red from blue

Generative:
Model each class probabilistically
Learn the parameters of each class from data
Generative Classification

Goal: Classify red from blue

Generative:
Model each class probabilistically
Learn the parameters of each class from data

For a test example \( x \), find \( P(\text{class 1}|x) \) and \( P(\text{class 2}|x) \)
Report 1 if \( P(\text{class 1}|x) > P(\text{class 2}|x) \), 2 otherwise
Discriminative Classification

Goal: Classify red from blue

Discriminative:
No need to model each class probabilistically
Find a suitable separator (say a linear separator) that mostly separates red from blue

Advantages and Disadvantages?
Generative vs. Discriminative

This class we will mostly cover discriminative models