Lecture 1: What is Machine Learning?

STAT161/261 Introduction to Pattern Recognition and Machine Learning Spring 2018 Prof. Allie Fletcher



Lecture 1 Outline

- Course information and details
- What and why machine learning?
- Supervised Learning
 - Examples
 - Classification
 - Regression
- Unsupervised Learning
- Reinforcement Learning
- Why now?



Course Info (see web; most significant bits here)

- We will be using CCLE, after enrollment settles down
- Instructor: Allie Fletcher
- Required Books: Introduction to Machine Learning by Ethem Alpaydin and Pattern Recognition and Machine Learning by Christopher Bishop
- The majority of what is important will be covered in lectured. However, you will be required to know readings, website handouts, and lecture--not just lecture
- Lecture notes may be slides and handwritten--union of both important :)

What is Machine Learning?

- Learn to improve algorithms from data
- Optimize a performance criterion using example data or past experience
- Role of Statistics: Inference from a sample
- Role of Computer science: Efficient algorithms to
 - Solve the optimization problem
 - Representing and evaluating the model for inference

Why "Learn"?

- Machine learning is programming computers to optimize a performance criterion using example data or past experience
- There is no need to "learn" to calculate payroll
- Learning is used when:
 - Human expertise does not exist (navigating on Mars)
 - Humans are unable to explain their expertise (speech recognition)
 - Solution changes in time (routing on a computer network)
 - Solution needs to be adapted to particular cases (user biometrics)

What We Talk About When We Talk About "Learning"

- Learning general models from a data of particular examples
- Data is cheap and abundant (data warehouses, data marts); knowledge is expensive and scarce
- Example in retail: Customer transactions to consumer behavior: *People who bought "Blink" also bought "Outliers" (www.amazon.com)*
- Build a model that is a good and useful approximation to the data

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Example 1: Digit Recognition



Images are 28 x 28 pixels

- Recognize a digit from the image
- Learn a function $f(x) \in \{0, 1, ..., 9\}$, x is a 28 x 28 matrix
- Expert systems do not work well:
 - You can recognize the digits, but difficult to program a function f(x) that works well
 - Try it!

Supervised Learning on Handwritten Digits

- Supervised:
 - Start with training data, labelled data
- Ex: 6000 examples of each digit
- Learn for example classifier f(x) that matches label well on training data
- Given new data *x* use function to guess digit
- Current systems get <0.21% errors (as of 1/20/2018)

http://rodrigob.github.io/are_we_there_yet/build/classification_dat asets_results.html#4d4e495354

- First commercial application:
 - Used by USPS for recognizing zip codes on letters

0	0	O	1	7	(1	7	1	г
Э	Z	2	æ	9	2	7	3	7	3
ζ	4	4	9	4	4	5	5	2	G
4	۷	7	2	٦	7	1	ટ	8	8
в	8	8	9	9	4	9	9	9	

Training examples Each sample must be labeled by hand who knows truth

Example 2: Credit Score and Classification

- Example: Credit score
- Determine/classify if customer is high-risk or low-risk
- Select some features:
 - Example: income & savings
 - Represent as a vector $x = (x_1, x_2)$
- Learn a function from features to target
 - Use past training data
 - Need to get this data
- The function on the right is an example of a decision tree. If savings are above a line, and then if income is above a line, then the candidate is low-risk.





Example 3: Spam Detection



- Classification problem:
 - Is email junk or not junk?
- For ML, must represent email numerically
 - Common model: bag of words
 - Enumerate all words, i = 1, ..., N
 - Represent email via word count x_i = num instances of word i
- Challenge:
 - Very high-dimensional vector
 - System must continue to adapt (keep up with spammers)

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Example 4: Face Detection



- Also a supervised learning problem
- For each image region, determine if
 - Face or non-face



Training Data

- Typical early face recognition datasets:
- 5000 faces
 - All near frontal
 - Vary age, race, gender, lighting
- 10⁸ non faces
- Faces are normalized (scale, translation)
- "functions" that work well may be very complex
- Many more datasets are available now:
 - See <u>http://www.face-rec.org/databases/</u>
 - You can use this for your project!





Rowley, Baluja and Kanade, 1998

Example 5: Stock Price Prediction



- Can you predict the price of a stock?
- What variables would you use?
- What is a non-machine learning approach?

Supervised Learning in General

- Prediction of future cases: Use the rule to predict the output for future inputs
- Knowledge extraction: The rule is easy to understand
- Compression: The rule is simpler than the data it explains
- Outlier detection: Exceptions that are not covered by the rule, e.g., fraud

Classification and SL: Many Applications

Aka Pattern recognition

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- Face recognition: Pose, lighting, occlusion (glasses, beard), make-up, hair style
- Character recognition: Different handwriting styles.
- Speech recognition: Temporal dependency.
- Medical diagnosis: From symptoms to illnesses
- Biometrics: Recognition/authentication using physical and/or behavioral characteristics: Face, iris, signature, etc

Regression

- Target variable *y* is continuous-valued
- Example:
 - Predict y = price of car
 - From *x* = mileage, size, horsepower,
 ...
 - Can use multiple predictors
- Assume some form of the mapping
 - Ex. Linear: $y = \beta_0 + \beta_1 x$
 - Find parameters β_0 , β_1 from data
- Note: predictors need not be cnts



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Regression Example

Machine Learning Repository

Center for Machine Learning and Intelligent Systems

Diabetes Data Set

Download: Data Folder, Data Set Description

File Names and format: (1) Date in MM-DD-YYYY format (2) Time in XX:YY format (3) Code (4) Value

The Code field is deciphered as follows:

33 = Regular insulin dose 34 = NPH insulin dose 35 = UltraLente insulin dose 48 = Unspecified blood glucose measurement 57 = Unspecified blood glucose measurement 58 = Pre-breakfast blood glucose measurement 59 = Post-breakfast blood glucose measurement 60 = Pre-lunch blood glucose measurement 61 = Post-lunch blood glucose measurement 62 = Pre-supper blood glucose measurement 63 = Post-supper blood glucose measurement 64 = Pre-snack blood glucose measurement 65 = Hypoglycemic symptoms 66 = Typical meal ingestion 67 = More-than-usual meal ingestion 68 = Less-than-usual meal ingestion 69 = Typical exercise activity 70 = More-than-usual exercise activity 71 = Less-than-usual exercise activity 70 - Hannahlad an adal arrant

- Predict blood glucose level
- Many possible predictors:
 - Recent past levels
 - Insulin dose
 - Time of last meal
 - • •
- Check out data in:

https://archive.ics.uci.edu/ml/datasets/D iabetes

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Unsupervised Learning

- Learning "what normally happens"
- No output
- Clustering: Grouping similar instances
- Example applications
 - Customer segmentation
 - Image compression: Color quantization
 - Bioinformatics: Learning motifs



Example: Document classification http://www.ibm.com/support/knowledgecenter /SSBRAM_8.7.0/com.ibm.classify.ccenter.doc/ c_WBG_Taxonomy_Proposer.htm

Reinforcement Learning

- Learning a policy: A sequence of outputs
- No supervised output but delayed reward
- Credit assignment problem
- Game playing
- Robot in a maze
- Multiple agents, partial observability, ...

What ML is Doing Today?

- Autonomous driving
- Jeopardy
- Very difficult games: Alpha
- Machine translation
- Many, many others...











Why Now?

- Machine learning is an old field
 - Much of the pioneering statistical work dates to the 19
- So what is new now?
- Big Data:
 - Massive storage. Large data centers
 - Massive connectivity
 - Sources of data from Internet and elsewhere
- Computational advances
 - Distributed machines, clusters
 - GPUs and hardware





Google Tensor Processing Unit (TPU)

Resources: Journals

- Journal of Machine Learning Research <u>www.jmlr.org</u>
- Machine Learning
- Neural Computation
- Neural Networks
- IEEE Trans on Neural Networks and Learning Systems
- IEEE Trans on Pattern Analysis and Machine Intelligence
- Journals on Statistics/Data Mining/Signal Processing/Natural Language Processing/Bioinformatics/...

Resources: Conferences

- International Conference on Machine Learning (ICML)
- European Conference on Machine Learning (ECML)
- Neural Information Processing Systems (NIPS)
- Uncertainty in Artificial Intelligence (UAI)
- Computational Learning Theory (COLT)
- International Conference on Artificial Neural Networks (ICANN)
- International Conference on AI & Statistics (AISTATS)
- Knowledge Discovery and Data Mining (KDD)
- International Conference on Computer Vision and Pattern Recognition (CVPR)
- International Conference on Computer Vision (ICCV)
- European Conference on Computer Vision (ECCV)

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Machine Learning in Almost All Fields

- Retail: Market basket analysis, Customer relationship management (CRM)
- Finance: Credit scoring, fraud detection
- Manufacturing: Control, robotics, troubleshooting
- Medicine: Medical diagnosis
- Telecommunications: Spam filters, intrusion detection
- Bioinformatics: Motifs, alignment
- Web mining: Search engines

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Objectives

- Provide examples of machine learning used today
- Given a new problem, qualitatively describe how machine learning can be used
 - Formulate a potential machine learning task
 - Identify the data needed for the task
 - Identify objectives
- Classify a machine learning task:
 - Supervised vs. unsupervised, regression vs. classification
- For supervised learning, identify the predictors and target variables
- Determine the role of expert knowledge in the task vs. data-driven learning