Course number: W207

Class 1 ...

Introduction

- Weekly schedule: (may change slightly)
 - Week 1: Kick-off course

Student introductions. Projects, assignments, requirements, breakout rooms, Introduction to Machine Learning.

Week 2: Nearest Neighbors

Tutorial notebook. Review NN lecture. NN notebook in breakout rooms.

Week 3: Naive Bayes and text classification

Discuss NB applications—spam (Graham), spelling (Norvig) in breakout rooms. NB Notebook in breakout rooms.

Week 4: Decision Tress and Ensembles

Review DT lecture. DT Notebook in breakout rooms.

Week 5: Deep breadth

Compare NN, NB, DT. Discuss AUC measure. Ensembles notebook in breakout room. Lecture review time permitting.

Week 6: Gradient Descent

Review GD. Final Project discussion. Regression Notebook in breakout rooms.

Week 7: Neural Networks

Review NN lecture. NN notebook part 1 in breakout rooms.

- Weekly schedule: (may change slightly)
 - Week 8: Applied SVMs and wrap-up of supervised learning
 Discussion of SVM libraries and their evolution. Comparison of algorithms learned so far. NN notebook part 2.
 - Week 9: Deep Learning
 Introduce convolutional nets (CNNs). K-means review. NN notebook part 3.
 - Week 10: Unsupervised learning.
 K-means (cont.). GMM review. Means notebook in breakout room.
 - Week 11: PCA and Case Study
 PCA review. Kaggle case study.
 - Week 12: Network Science
 Group discussion of network science, algorithms, visualizations, and different tools.
 - Week 13: Recommendations and Personalization
 Group discussions, paper review, share experience.
 - Week 14: Student Presentations

Methods of Instruction

Lectures, presentations and in-class discussions will be the main tools of instruction. Students should read the asynch material provided prior to the live class sessions.

Course Grade Weighting

Final grades will be based on

– 3 Projects: 60% - individual

Final project: 35% - group

Participation: 5% - individual

Students can meet up in Slack

Programming projects:

- This course includes 3 guided programming projects. They will distributed at the
 beginning of the course and should be submitted (via github) by the beginning of
 your live session in the week specified below. They will involve filling in relatively
 short pieces of code in a python notebook and sometimes brief analysis of results.
- Late submissions will be accepted up to 1 week past the deadline with a 10% penalty, but you need to let your instructor know if you'll be submitting late.
- You may work alone or in groups but you need to write your own code. Discussion, especially about programming issues, on the wall is encouraged.

Project 1 Due: Week 5

Project 2 Due: Week 9

Project 3 Due: Week 13

Final project:

- At the midway point in the course, your instructor will share details about the final project. You'll choose from a list of relevant Kaggle competitions, run experiments, write up a notebook summarizing your work and key results, and give a short presentation in the final live session. You are strongly encouraged to work in groups.
- Baseline submission: Week 10
- Check-in with instructor: Week 12
- Notebook due and in-class presentation: Week 14
- The code for all problem set is posted here:
 https://github.com/smiletodaywithme/W207-Applied-Machine-Learning/tree/master/Projects

Programming environment:

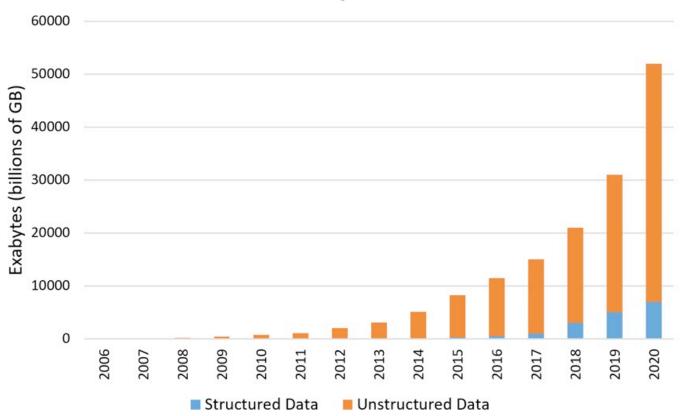
- All the projects should run fine on your personal computer. Install python, ipython notebook, numpy, matplotlib, and scikits.learn. A number of other useful packages will be introduced during the semester.
- Both Enthought and Anaconda are free python distributions that include all the relevant packages.

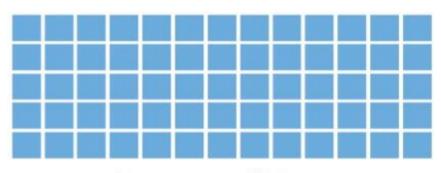
- Class 1 outline:
 - Projects, assignments and requirements
 - Data Mining vs Machine Learning
 - What is Machine Learning?
 - Supervised vs. Unsupervised Learning
 - Supervised learning methods: (mostly used in this class)
 - kNN one of the earliest algorithms, using distance between observations
 - Naive Bayes using Bayes theorem, estimating the probability of a class label, used in text analysis
 - Decision trees random forests, gradient boosted trees, one of the most useful methods
 - Regression (linear and logistic) used in finance and in the business world
 - Regularization estimating sparse models (more attributes than observations)
 - Optimization using gradient descent how to estimate parameters in models like NN, just like backpropagation
 - Neural Networks with backpropagation introducing nonlinearity for solving more complex problems
 - Unsupervised learning methods:
 - Clustering k-means, clustering
 - PCA dimensionality reduction (ex. healthcare: disease prediction)
 - EM (Expectation Maximization) algorithms and Mixture Models discover the mean and covariance of each cluster assuming Gaussian distribution
 - Overfitting making the model too complex to be applied in the real world
 - Data source Kaggle.com

Data:

- We are overwhelmed with data. The amount of data in the world is ever more increasing and there is no end to it
- According to IDC Research:
 - digital data will grow at a compound annual growth rate (CAGR) of 42% through 2020
 - in the 2010-2020 decade, the world's data will grow by 50X; i.e., from about 1ZB in 2010 to about 50ZB in 2020

The Cambrian Explosion...of Data





Structured Data



Graphical representations illustrate the difference between structured and unstructured data

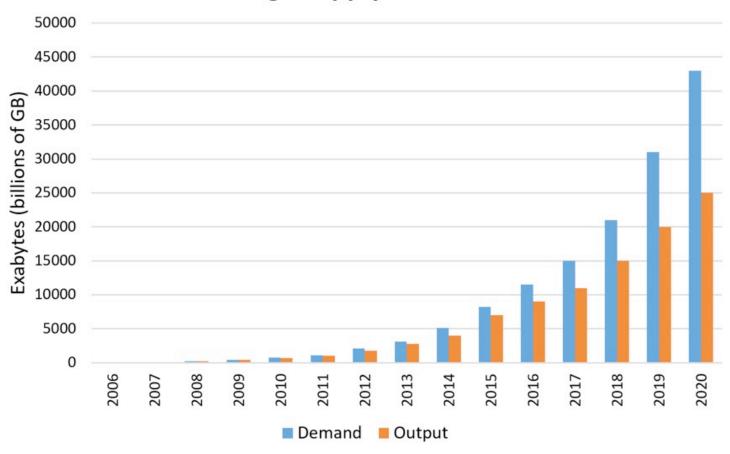
Multiplying Factor	SI Prefix	Scientific Notation	Name
1 000 000 000 000 000 000 000 000	Yotta (Y)	1024	1 septillion
1 000 000 000 000 000 000 000	Zetta (Z)	1021	1 sextillion
1 000 000 000 000 000 000	Exa (E)	10 ¹⁸	1 quintillion
1 000 000 000 000 000	Peta (P)	10 ¹⁵	1 quadrillion
1 000 000 000 000	Tera (T)	1012	1 trillion
1 000 000 000	Giga (G)	10 ⁹	1 billion
1 000 000	Mega (M)	10 ⁶	1 million
1 000	kilo (k)	10 ³	1 thousand
0 001	milli (m)	10-3	1 thousandth
0 000 001	micro (u)	10-6	1 millionth
0 000 000 001	nano (n)	10 ⁻⁹	1 billionth
0 000 000 000 001	pico (p)	10-12	1 trillionth
0 000 000 000 000 001	femto (f)	10 ⁻¹⁵	1 quadrillionth
0 000 000 000 000 000 001	atto (a)	10 ⁻¹⁸	1 quintillionth
0 000 000 000 000 000 000 001	zepto (z)	10-21	1 sextillionth
0 000 000 000 000 000 000 000 001	yocto (y)	10-24	1 septillionth

Metric prefixes defined at the 19th General Conference on Weights and Measures in 1991

Multiplying Factor	SI Prefix	Scientific Notation	Name
1 208 925 819 614 629 174 706 176	Yottabytes	280	1 septillion
1 180 591 620 717 411 303 424	Zettabytes	270	1 sextillion
1 152 921 504 606 846 976	Exabytes	260	1 quintillion
1 125 899 906 842 624	Petabytes	250	1 quadrillion
1 099 511 627 776	Terabytes	240	1 trillion
1 073 741 824	Gigabytes	230	1 billion
1 048 576	Megabytes	2 ²⁰	1 million
1 024	kilobytes	210	1 thousand

Examples of prefixes used to measure digital data with a binary system

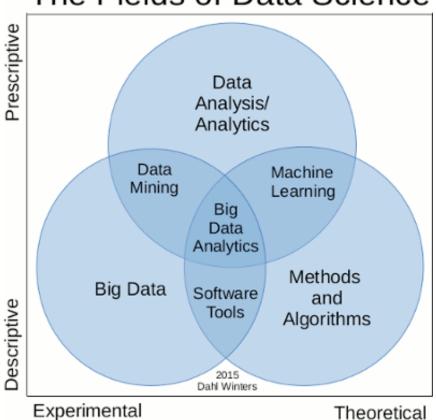
Storage Supply & Demand

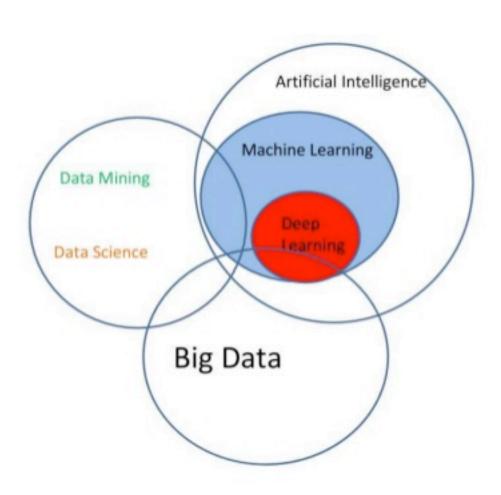


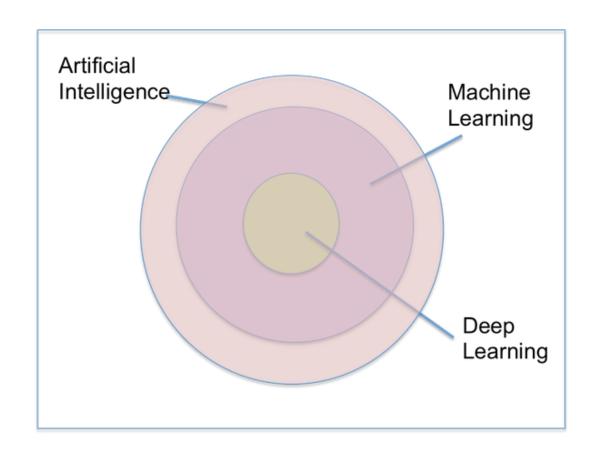
Storage supply and demand growth over two decades

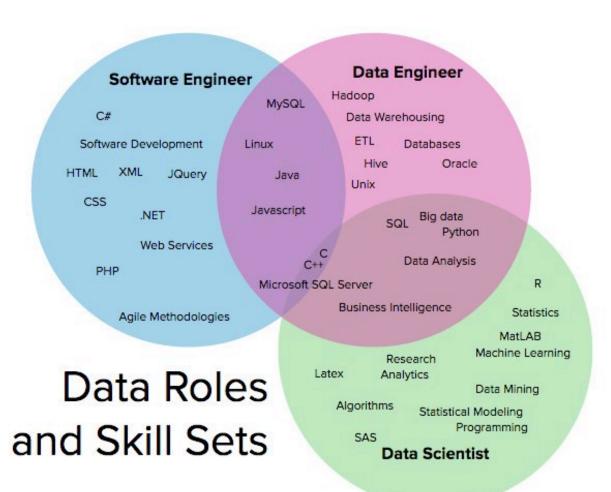
What is the difference between Data Science, Data Analysis, Big Data, Data Analytics, Data Mining and Machine Learning? **Data Science** Deals with structured and unstructured data Everything that **Data Analysis** relates to data cleansing, prepara-Huge data volumes that cannot tion and analysis Human activities be processed effectively with aimed at gaining traditional applications some insight on a Begins with raw data that is datasetanalysis not aggregated and it is often impossible to store such data **Data Analytics** in the memory of a single Automating insights into a Analystican use dataset and supposes the some Data Analytusage of gueries and data ics tools to obtain aggregation procedures desired results, but in principle, Data **Data Mining** Can represent various Analysis can be dependencies between performed without input variables, but also special data Uses the predictive force of can use Data Mining processing machine learning by applying techniques and tools to Machine Learning various machine learning discover hidden patterns algorithms to Big Data in the dataset under Artificial intelligence technique analysis that is broadly used in Data Mining Uses a training dataset to build a model that can predict values of target variables Source: onthe.io

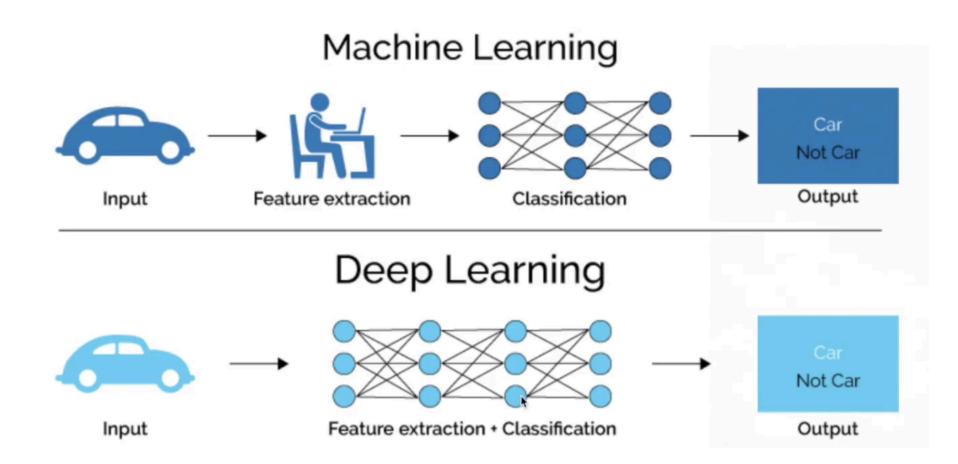
The Fields of Data Science











Data Mining

- What is Data Mining?
 - Data mining is defined as the process of discovering patterns in data
 - Data mining is about solving problems by analyzing data already present in datasets / databases
 - In data mining, the data is stored electronically and the search is automated
 - It has been estimated that the amount of data stored in the world's databases doubles every 20 months

- What is machine learning...? (recall)
- The dictionary defines "to learn" as:
 - To get knowledge of something by study, experience, or being taught
 - To become aware by information or from observation
 - To commit to memory
 - To be informed of or to ascertain
 - To receive instruction

- Definitions of "learning" from dictionary:
 - To get knowledge of by study, experience, or being taught
 - To become aware by information or from observation
 - To commit to memory
 - To be informed of, ascertain; to receive instruction

Difficult to measure

Trivial for computers

Operational definition:

What is it?

Does a slipper learn?

Does learning imply intention?

- What is machine learning?
- An operational definition can be formulated in the same way for learning:
 - Things learn when they change their behavior in a way that makes them perform better in the future
- This ties learning to performance rather than knowledge
- You can test learning by observing present behavior and comparing it with past behavior

- What is machine learning?
- ... However, learning is a rather slippery concept. Lots of things change their behavior in ways that make them perform better in the future, yet we wouldn't want to say that they have actually learned.

... back to the *comfortable slipper* - has it learned the shape of your foot? It has certainly changed its behavior to make it perform better as a slipper! Yet we would hardly want to call this learning

- What is *machine learning?*
- ... We therefore choose the word training to denote a mindless kind of learning
- We train animals and even plants, although it would be stretching the word a bit to talk of training objects such as slippers, which are not in any sense alive
- ... But learning is different. Learning implies thinking and purpose.
- Something that learns has to do so intentionally
- That is why we wouldn't say that a vine has learned to grow around a trellis in a vineyard—we'd say it has been trained
- Learning without purpose is merely training

- Artificial Intelligence concept
 - It is a concept conceived in the mid 50s with the intention to construct complex machines (computers) that possessed the same characteristics of human intelligence
 - The main idea is to create technologies able to perform specific tasks better than humans can
 - Some of the first intelligent robots emerged in movies such as Star Wars C-3PO
 - Artificial intelligence (AI) is already part of our everyday lives
 - Some examples of AI are: image classification, face recognition, voice recognition, speaker recognition, emotion recognition, etc.

- Data Mining and Machine Learning concepts
 - In data mining, the data is stored electronically and the search is automated (or semiautomated)
 - It has been estimated that the amount of data stored in the world's databases doubles every 20 months ...
 - ... Thus the opportunities for data mining increase
 - Data mining is about solving problems by analyzing data already present in databases
 - Data mining finds patterns that can be analyzed to identify distinguishing characteristics

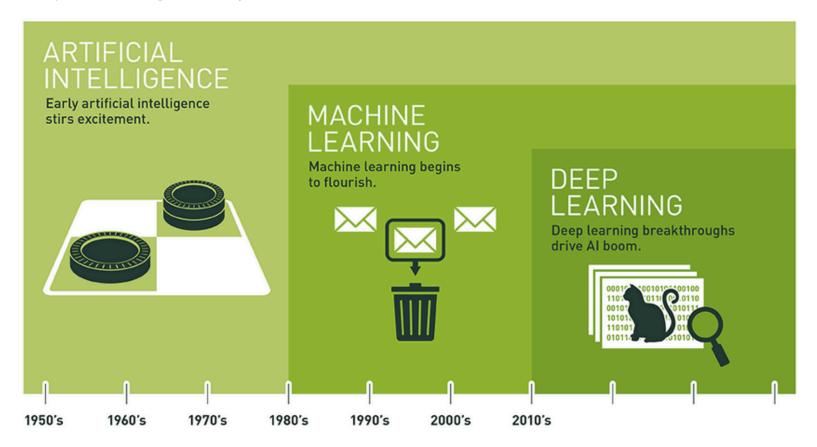
- Data Mining and Machine Learning concepts
 - Machine learning came directly from the early AI scientists. The algorithmic approaches over the years included: decision tree learning, logic programming, clustering, reinforcement learning, Bayesian networks, etc.
 - To "learn" by definition for us humans means to:
 - Obtain knowledge of something and being aware of something
 - Be informed, receive instructions, commit to memory
 - An operational definition for "learn" can be formulated like:
 - Things learn when they change their behavior in a way that makes them perform better in the future. The definition of "better" is given by us and means "performance" rather than "knowledge"

Data Mining and Machine Learning concepts

- Machine learning does not entail the conceptual limitations mentioned herein, and disregards any particular philosophical stance about what learning actually is
- Machine learning is therefore a practical process connected to Data mining while using algorithms to parse data, learn from it, and then make a prediction
- Performance:
 - the machine is "trained" using large amounts of data and algorithms that give it the ability to learn;
 - it is then "tested" on a new (usually unknown) set of data

- Deep Learning concept
 - Deep Learning is an area in Machine Learning that has been introduced with the objective of moving Machine Learning closer to its goal: Artificial Intelligence
 - Deep Learning has enabled many practical applications of Machine Learning and by extension the overall field of AI
 - Deep Learning breaks down tasks in ways that makes all kinds of machine assists seem possible
 - Areas of implementation are infinite, but some of them are: preventive healthcare, security systems, robotics, cars without drivers, better media recommendations, etc.

Deep Learning concept



source: nvidia.com

Describing Structural Patterns:

- What are structural patterns?
- How do we describe structural patterns?
- What do they look like?

Structural descriptions

• Example: if-then rules

```
If tear production rate = reduced
  then recommendation = none
Otherwise, if age = young and astigmatic = no
  then recommendation = soft
```

Age	Spectacle prescription	Astigmatism	Tear production rate	Recommended lenses
Young	Муоре	No	Reduced	None
Young	Hypermetrope	No	Normal	Soft
Pre-presbyopic	Hypermetrope	No	Reduced	None
Presbyopic	Myope	Yes	Normal	Hard

• Describing Structural Patterns: contact lens dataset

Age	Spectacle Prescription	Astigmatism	Tear Production Rate	Recommended Lenses
young	myope	no	reduced	none
young	myope	no	normal	soft
young	myope	yes	reduced	none
young	myope	yes	normal	hard
young	hypermetrope	no	reduced	none
young	hypermetrope	no	normal	soft
young	hypermetrope	yes	reduced	none
young	hypermetrope	yes	normal	hard
pre-presbyopic	myope	no	reduced	none
pre-presbyopic	myope	no	normal	soft
pre-presbyopic	myope	yes	reduced	none
pre-presbyopic	myope	yes	normal	hard
pre-presbyopic	hypermetrope	no	reduced	none
pre-presbyopic	hypermetrope	no	normal	soft
pre-presbyopic	hypermetrope	yes	reduced	none
pre-presbyopic	hypermetrope	yes	normal	none
presbyopic	myope	no	reduced	none
presbyopic	myope	no	normal	none
presbyopic	myope	yes	reduced	none
presbyopic	myope	yes	normal	hard
presbyopic	hypermetrope	no	reduced	none
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presbyopic	hypermetrope	yes	reduced	none
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pre-presbyopic	myope	yes	normal	hard
pre-presbyopic	hypermetrope	no	reduced	none
pre-presbyopic	hypermetrope	no	normal	soft
pre-presbyopic	hypermetrope	yes	reduced	none
pre-presbyopic	hypermetrope	yes	normal	none
presbyopic	myope	no	reduced	none

If tear production rate = reduced then recommendation = none Otherwise, if age = young and astigmatic = no then recommendation = soft

presbyopic hypermetrope no normal soft presbyopic hypermetrope yes reduced none presbyopic hypermetrope yes normal none

Describing Structural Patterns:

- Structural descriptions do not necessarily need to be expressed as rules such as these
- Decision trees, specify the sequences of decisions that need to be made along with the resulting recommendation, are another popular means of expression

- Describing Structural Patterns:
 - The rules do not generalize from the data; they merely summarize it
 - In most learning situations, the set of examples given as input is far from complete, and part of the job is to generalize to other, new examples

So:

Imagine omitting some of the rows in a table for which the tear production rate is reduced and still coming up with the rule ..
 .. (see next slide)

• Describing Structural Patterns: contact lens dataset

hypermetrope yes

presbyopic

Age	Spectacle Prescription	Astigmatism	Tear Production Rate	Recommended Lenses
young	myope	no	reduced	none
young	myope	no	normal	soft
young	myope	yes	reduced	none
young	myope	yes	normal	hard
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young	hypermetrope	no	normal	soft
young	hypermetrope	yes	reduced	none
young	hypermetrope	yes	normal	hard
pre-presbyopic	myope	no	reduced	none
pre-presbyopic	myope	no	normal	soft
pre-presbyopic	myope	yes	reduced	none
pre-presbyopic	myope	yes	normal	hard
pre-presbyopic	hypermetrope	no	reduced	none

If tear production rate - reduced then recommendation - none pre-presbyopic hypermetrope normal none reduced If tear production rate = reduced then recommendation = none Otherwise, if age = young and astigmatic = no then recommendation = soft normal soft presbyopic hypermetrope no presbyopic reduced hypermetrope none

normal

none

- Describing Structural Patterns:
 - First, this would generalize to the missing rows
 - Second, values are specified for all the features in all the examples.
 Real-life datasets invariably contain values of some features, for some reason or other, are unknown—for example, measurements were not taken or were lost
 - Third, the preceding rules classify the examples correctly, whereas
 often, because of errors or noise in the data, misclassifications
 occur even on the data that is used to create the classifier

attributes = features = predictors

examples = instances = variables

sunny,85,85,FALSE	no
sunny,80,90,TRUE	no
overcast,83,86,FALSE	ye
rainy,70,96,FALSE	ye
rainy,68,80,FALSE	ye
rainy,65,70,TRUE	no
overcast,64,65,TRUE	ye
sunny,72,95,FALSE	no
sunny,69,70,FALSE	ye
rainy,75,80,FALSE	ye
sunny,75,70,TRUE	ye
overcast,72,90,TRUE	ye
overcast,81,75,FALSE	ye
rainy,71,91,TRUE	no

class = outcome

- Class 1 recap:
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 - Neural Networks with backpropagation introducing nonlinearity for solving more complex problems
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 - PCA dimensionality reduction (ex. healthcare: disease prediction)
 - EM (Expectation Maximization) algorithms soft clustering and Mixture Models discover the mean and covariance of each cluster using probability assuming Gaussian distribution
 - Overfitting making the model too complex to be applied in the real world
 - Data source Kaggle.com