Data Representation
Testing and evaluation schemes
Labs and Tools
Data Set Features

- **Data Types**
  - Nominal (aka Categorical, Discrete)
  - Continuous (aka Real, Numeric)
  - Linear (aka Ordinal) – Is usually just treated as continuous, so that ordering info is maintained

- **Consider a Task:** Classifying the quality of pizza
  - What features might we use? Do one of each versions above.

- **How to represent those features?**
  - Will usually depend on the learning model we are using

- **Classification assumes the output class is nominal. If output is continuous, then we are doing regression.**
Fitting Data to the Model

- Continuous -> Nominal
  - Discretize into bins – more on this later

- Nominal -> Continuous (Perceptron expects continuous)
  a) One input node for each nominal value where one of the nodes is set to 1 and the other nodes are set to 0 – One Hot
     - Can also explode the variable into \( n-1 \) input nodes where the most common value is not explicitly represented (i.e. the all 0 case)
  b) Use 1 node but with a different continuous value representing each nominal value
  c) Distributed – \( \log_b n \) nodes can uniquely represent \( n \) nominal values (e.g. 3 binary nodes could represent 8 values)
  d) If there is a very large number of nominal values, could cluster (discretize) them into a more manageable number of values and then use one of the techniques above

- Linear data is already in continuous form
Data Normalization

What would happen if you used two input features in an astronomical task as follows:

- Weight of the planet in grams
- Diameter of the planet in light-years
Data Normalization

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Normalize the Data between 0 and 1 (or similar bounds)
- For a specific instance, could get the normalized feature as follows:
  \[ f_{\text{normalized}} = \frac{f_{\text{original}} - \text{Minvalue}_{TS}}{\text{Maxvalue}_{TS} - \text{Minvalue}_{TS}} \]

Use these same Max and Min values to normalize data in novel instances

Pandas and Sklearn have simple methods to do this and other normalization approaches

Note that a novel instance may have a normalized value outside 0 and 1
- Why? Is it a big issue?
ARFF Files

An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a Machine Learning dataset (or relation).
- Developed at the University of Waikato (NZ) for use with the Weka machine learning software (http://www.cs.waikato.ac.nz/~ml/weka).
- We will commonly use the ARFF format for CS 270

ARFF files have two distinct sections:
- Metadata information
  - Name of relation (Data Set)
  - List of attributes and domains
- Data information
  - Actual instances or rows of the relation

Optional comments may also be included which give information about the Data Set (lines prefixed with %)
Sample ARFF File

% 1. Title: Pizza Database
% 2. Sources:
%      (a) Creator: BYU CS 270 Class…
%      (b) Statistics about the features, etc.

@RELATION Pizza

@ATTRIBUTE Weight real
@ATTRIBUTE Crust {Pan, Thin, Stuffed}
@ATTRIBUTE Cheesiness real
@ATTRIBUTE Meat {True, False}
@ATTRIBUTE Quality {Good, Great}

@DATA
.9, Stuffed, 99, True, Great
.1, Thin, 2, False, Good
?, Thin, 60, True, Good
.6, Pan, 60, True, Great

Any column could be the output, but we will assume that the last column(s) is the output

Assume cheesiness is linear (an integer between 0 and 100)

What would you do to this data before using it with a perceptron and what would the perceptron look like? – Show an updated ARFF row
ARFF Files

- More details and syntax information for ARFF files can be found at our website
- Also have a small arff library to help you out
- Data sets that we have already put into the ARFF format can also be found at our website and linked to from the LS content page

   http://axon.cs.byu.edu/data/

- You will use a number of these in your simulations throughout the semester – Always read about the task, features, etc, rather than just plugging in the numbers
- You will create your own ARFF files in some projects, and particularly with the group project
Performance Measures

There are a number of ways to measure the performance of a learning algorithm:
- Predictive accuracy of the induced model (or error)
- Size of the induced model
- Time to compute the induced model
- etc.

We will focus mostly on accuracy/error

Fundamental Assumption:

*Future novel instances are drawn from the same/similar distribution as the training instances*
Training/Testing Alternatives

- Four methods that we commonly use:
  - Training set method
  - Static split test set
  - Random split test set CV
  - $N$-fold cross-validation
  - The last two are the more accurate approaches
Training Set Method

Procedure
- Build model from the training set
- Compute accuracy on the same training set

Simple but least reliable estimate of future performance on unseen data (a rote learner could score 100%!)

Not used as a performance metric but it is often important information in understanding how a machine learning model learns

This is information which you will often report in your labs and then compare it with how the learner does on a better method
Static Training/Test Set

Static Split Approach
- The data owner makes available to the machine learner two distinct datasets:
  - One is used for learning/training (i.e., inducing a model), and
  - One is used exclusively for testing

Note that this gives you a way to do repeatable tests
Can be used for challenges (e.g. to see how everyone does on one particular unseen set, method we use for helping grade your labs.)
Be careful not to overfit the Test Set (“Gold Standard”)
Cross-Validation (CV) – Cross-validation is a resampling method that uses different portions of the data to test and train a model on different iterations.

We then average the results of these iterations.

With CV we avoid having data just used for either training or test, and give all data a chance to be part of each, thus getting more accurate results.
Random Training/Test Set Approach

Random Split CV Approach (aka holdout method)
- The data owner makes available to the machine learner a single dataset
- The machine learner splits the dataset into a training and a test set, such that:
  - Instances are randomly assigned to either set
  - The distribution of instances (with respect to the target class) is hopefully similar in both sets due to randomizing the data before the split
    - Stratification is an option to ensure proper distribution
  - Typically 60% to 90% of instances is used for training and the remainder for testing – the more data there is the more that can be used for training and still get statistically significant test predictions
  - Useful quick estimate for computationally intensive learners
  - Not statistically optimal (high variance, unless lots of data)
    - Could get a lucky or unlucky test set
  - Best to do multiple training runs with different random splits. Train and test $m$ different splits and then average the accuracy over the $m$ runs to get a more statistically accurate prediction of generalization accuracy.
N-fold Cross-validation

- Use all the data for both training and testing
  - Statistically more reliable
  - All data can be used which is good, especially for small data sets

Procedure
- Partition the randomized dataset (call it $D$) into $N$ equally-sized subsets $S_1, \ldots, S_N$
- For $k = 1$ to $N$
  - Let $M_k$ be the model induced from $D - S_k$
  - Let $a_k$ be the accuracy of $M_k$ on the instances of the test fold $S_k$
- Return $(a_1 + a_2 + \ldots + a_N)/N$
$N$-fold Cross-validation (cont.)

- The larger $N$ is, the smaller the variance in the final result.
- The limit case where $N = |D|$ is known as leave-one-out CV and provides the most reliable estimate. However, it is typically only practical for small instance sets.
- Commonly, a value of $N=10$ is considered a reasonable compromise between time complexity and reliability.
- Still must choose an actual model to use during execution – how?
$N$-fold Cross-validation (cont.)

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- Still must chose an actual model to use during execution - how?
  - Could select the one model that was best on its fold?
  - All data! With any of the approaches.
- Note that $N$-fold CV is just a better way to estimate how well we will do on novel data, rather than a way to do *model selection*. 
Machine Learning Tools

Lots of new Machine Learning Tools
- Weka was the first main site with lots of ready to run models
- Scikit-learn now very popular
- Languages:
  - Python with NumPy, matplotlib, pandas, other libraries
  - R (good statistical packages), but with growing Python libraries...
- Deep Learning Neural Network frameworks – GPU capabilities
  - Tensorflow - Google
  - PyTorch – Multiple developers (Facebook, twitter, Nvidia...) - Python
  - Others: Caffe2 (Facebook), Keras, Theano, CNTK (Microsoft)
- Data Mining Business packages – Visualization, Expensive

Great for experimenting and applying to real problems
But important to “get under the hood” and not just be black box ML users
Doing Your Labs

- Will use scikit-learn in individual labs
  - Whatever you want in group project
- Program in Python in Jupyter notebooks
  - NumPy library – Great with arrays, etc.
- Recommended tools and libraries
  - Colab – Google IDE for Python and Jupyter notebooks
  - Pandas – Data Frames and tools are very convenient
  - Matplotlib
scikit-learn (SK)

- One of the most used and powerful machine learning toolkits out there
- Lots of implemented models and tools to use for machine learning applications
  - Sometimes missing some things we would like, but it is continually evolving
  - Source is available, and you can always override methods with your own, etc.
- Basically a Python Library to call from your Python code
- Familiarize yourself with the scikit-learn website as you will be using it for all labs
Perceptron Project

- Content Section of LS (Learning Suite) for project specifications
  - Review carefully the introductory part regarding all projects
- For each project carefully read the specifications for the lab in the Jupyter notebook on GitHub
- You can just copy the Perceptron notebook from the GitHub site to your computer and then add your work in the code and text boxes