Machine Learning
A Brief & Spotty Survey

L715/B659
(with many thanks to Sandra Kübler!)

Dept. of Linguistics, Indiana University
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Machine learning explores the study and construction of algorithms that can learn from and make predictions on data. (https://en.wikipedia.org/wiki/Machine_learning, retrieved 8/22/16)

- Our focus will be on supervised learning, where the ML system learns from labeled examples
  - There will be some space for unsupervised learning, too
Motivation for ML in computational linguistics:

- Manually developed NLP systems and language resources for NLP
  - require considerable human effort
  - are often based on limited inspection of the data with an emphasis on prototypical examples
    - (... though, precision can be quite high)
  - often fail to reach sufficient domain coverage
  - often lack sufficient robustness when input data is noisy

These issues are exacerbated with a task such as author profiling across different domains.
Motivation for ML in CL (2)

In contrast:

- NLP systems and language resources for NLP based on machine learning techniques
  - require less human effort
  - are data-driven & require large-scale data sources
  - achieve coverage directly proportional to the richness of the data source
  - are more adaptive to noisy data

One priority for us, then, is to obtain appropriate data (more on that in the coming weeks)

- Adapting to new domains is also a challenge
Machine Learning

**Idea:** computers are better at finding regularities than humans

- Do not give the computer explicit rules
- Let it extract knowledge from data

**Assumptions of learning:**

- From labeled data $\rightarrow$ supervised learning
- From unlabeled data $\rightarrow$ unsupervised learning

**Ways to approach the problem:**

- Abstract over data $\rightarrow$ eager learning
- Do not abstract over data $\rightarrow$ lazy learning
Classification

- Classification:
  - Supervised learning ≈ classification
  - Classification = assigning a label from a limited set of labels to an instance
  - Instance = pre-defined list of feature-value pairs
- Unsupervised approaches: more general results (hierarchies, models)

We may also want to employ **ranking** amongst choices
- May be as simple as comparing classifier confidence for multiple guesses
- Makes the most sense for gradient properties
Example: Part-of-Speech Tagging

- Task: find the appropriate POS tag for a word in context

- e.g., They \texttt{man}_{VB} the boat. vs. They \texttt{man}_{NN} in the boat.
  - for English, accuracy $> 96\%$
  - for morphologically rich languages: many POS tags

Sample instance:

<table>
<thead>
<tr>
<th>feature</th>
<th>word$_2$</th>
<th>tag$_2$</th>
<th>word$_1$</th>
<th>tag$_1$</th>
<th>word</th>
<th>POS tag</th>
</tr>
</thead>
<tbody>
<tr>
<td>value</td>
<td>NULL</td>
<td>NULL</td>
<td>They</td>
<td>PRP</td>
<td>man</td>
<td>VB</td>
</tr>
</tbody>
</table>
Our task this semester falls under the general field of document classification, or text classification:

- text classification ⊂ classification ⊂ machine learning
- Classification might be in terms of topics/subjects, document type, etc.
  - Generally different from our task, documents may contain multiple topics (any-of problem)
  - Topics may also be hierarchical, e.g., poultry and coffee as subclasses of industries
- Some useful links:
The Learning Problem

- **instance**: a vector of feature values \(< f_1, f_2, \ldots, f_n >\) where the values are taken from the discrete or real-valued domain of the \(i\)th feature

- let \(X\) be the space of possible instances

- let \(Y\) be the set of classes

  - the goal of the ML system is to learn a **target function** \(c : X \rightarrow Y\)
Some learners require real-valued features, while some (e.g., timbl) allow for things like text features

Text features:

<table>
<thead>
<tr>
<th>Per</th>
<th>Num</th>
<th>Gen</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>pl</td>
<td>neut</td>
<td>1</td>
</tr>
</tbody>
</table>

Real-valued features:

<table>
<thead>
<tr>
<th>Per</th>
<th>Num</th>
<th>Gen</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sg</td>
<td>Pl</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Likewise, some learners require binary decisions

▶ though, they usually have techniques to convert $n$-ary decisions to binary internally
The Learning Problem (3)

- **Training example:** instance $x \in X$ labeled with the correct class $c(x)$

  - let $D$ be the set of all training examples

- **Hypothesis space**, $H$: set of functions $h : X \rightarrow Y$ of possible definitions

  - the goal is to find an $h \in H$ such that for all $<x, c(x)> \in D$, $h(x) = c(x)$
Some Important Concepts

- generalization: generalize from experience
- abstraction
  - vs. lazy learning: generalize when needed
  - non-abstraction can be useful when there are many exceptions & sub-regularities
- online learning: learn one instance at a time & thus continually refine model
- offline learning: learn as a batch
Some Machine Learning Algorithms

Supervised:

- decision tree learning
- memory-based learning (k-nearest neighbors)
- support vector machines (SVM)
- maximum entropy learning
- neural networks
- genetic programming
- naive Bayes

Unsupervised:

- clustering
- minimum description length
Evaluation

- **Training set**: data on which the ML program is trained
- **Test set**: data on which the performance of the ML program is measured
  - **Gold standard**: data against which the ML program is evaluated
- **(Tenfold) Cross validation**: split data into 10 parts:
  - 10 rounds: use 1 part as test set and remaining parts as training set
Evaluation Metrics

Common metrics include:

- **Accuracy**: percentage of correctly classified instances from test set
- **Recall**: percentage of the items in the gold standard that were found by the ML program
- **Precision**: percentage of the items selected by the ML program that are correct

Sometimes also: sensitivity, specificity, area under the ROC curve (http://gim.unmc.edu/dxtests/roc3.htm), ...
Useful comparisons by which to gauge results:

- **Baseline**: simple method, often heuristic; gives the lower estimate of the difficulty of the problem
  - Note in the PAN data sets how baseline systems are included
- **Upper bound**: what can be reached in the optimal case, often human performance
  - For some tasks (e.g., detecting deception), human performance may be below automatic systems
Problems with ML

- Difficult to distinguish between noise and subregularities / irregularities
- Feature selection mainly by intuition
  - Though, see, e.g., deep learning (http://nlp.stanford.edu/courses/NAACL2013/)
  - Irrelevant information can deteriorate performance
- Skewed class distribution deteriorates performance
- Some tasks defined as classification may not naturally be classification
Do’s and Don’t’s in ML

Don’t:
▶ report without evaluation
▶ test on (any part of) your training set

Do:
▶ make your features independent (required for most algorithms)
▶ optimize your parameters
▶ optimize features & parameters at the same time
  ▶ comparisons of learning algorithms are only meaningful if both are optimized
▶ beware of overfitting
▶ do what you can to get more data
Some Available Packages

Packages of multiple algorithms:

- weka (http://www.cs.waikato.ac.nz/ml/weka/)
- mallet (http://mallet.cs.umass.edu): MAchine Learning for LanguagE Toolkit
- MLlib (https://spark.apache.org/mllib/): good for very large-scale learning
- MLPack (http://www.mlpack.org): “emphasis on scalability, speed, and ease-of-use”
- sofia-ml (https://code.google.com/p/sofia-ml/)
More packages

- Python Machine Learning kits:
  - Orange: http://orange.biolab.si/
  - mlpy: https://mlpy.fbk.eu/
  - PyML: http://pyml.sourceforge.net/
  - Anaconda Python has much pre-installed: https://store.continuum.io/cshop/anaconda/

- Various packages in R (http://cran.r-project.org/web/views/MachineLearning.html)


- ...
Choosing a Classifier

Bias & Variance

- **Bias**: (non-)ability to approximate the data, degree to which model makes assumptions about data distribution
  - “High bias is related to under-fitting” (e.g., linear regression for a quadratic relationship)
- **Variance**: (non-)stability in the face of new training examples
  - “High variance is related to over-fitting” (e.g., k-NN changes a lot depending on training set)
- Regularization parameters help control bias-variance tradeoff
  - e.g., penalize complex models, set $k$ higher

(http://followthedata.wordpress.com/2012/06/02/practical-advice-for-machine-learning-bias-variance/)
Choosing a Classifier

Accounting for bias & variance

What to do? (originally from Andrew Ng)

▶ High variance?
  ▶ get more training examples
  ▶ try smaller sets of features

▶ High bias?
  ▶ try new (more/different) features

To find whether it’s high variance or bias, compare training & testing (i.e., development) learning curves:

▶ cf. slides 7 & 8 of:

(http://followthedata.wordpress.com/2012/06/02/practical-advice-for-machine-learning-bias-variance/)
Choosing a classifier

Some advice from Manning, Raghavan, & Schütze (2008):

▶ Can use rules, if the task is relatively simple
  ▶ Rules can also work well for post-processing ML output
▶ If you have little data, use a classifier with high bias (e.g., Naive Bayes)
  ▶ Also can try semi-supervised training methods (e.g., bootstrapping, EM)
▶ If you have a huge amount of data, the classifier may have less of an impact on accuracy
  ▶ Speed & ease of use become bigger questions

Other Ways to Boost Performance

- Combine multiple classifiers
- Engage in feature engineering
  - Group together similar features (i.e., with similar votes)
  - Create new features for potentially informative concepts (e.g., subwords)
- Account for document structure (e.g., upweight items in a title, use separate feature spaces for different document zones)

Next time

We’ll spend some time getting into practical matters
  ▶  See your assignment for installations