Machine Learning for Language Technology 2015

http://stp.lingfil.uu.se/~santinim/ml/2015/ml4lt_2015.htm

Machine Learning in Practice (2)

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Autumn 2015

Acknowledgements

- Weka’s slides
- Feature engineering: http://machinelearningmastery.com/discover-feature-engineering-how-to-engineer-features-and-how-to-get-good-at-it/
- - Daume' III (2015): 53-64
  - Witten et al. (2011): 147-156

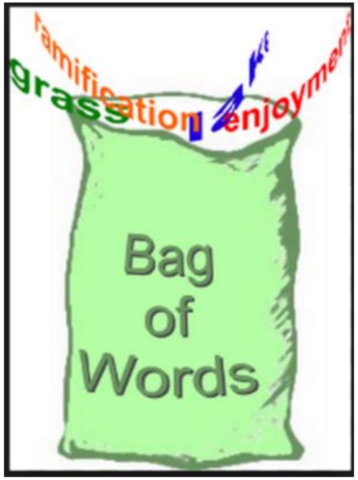
Outline

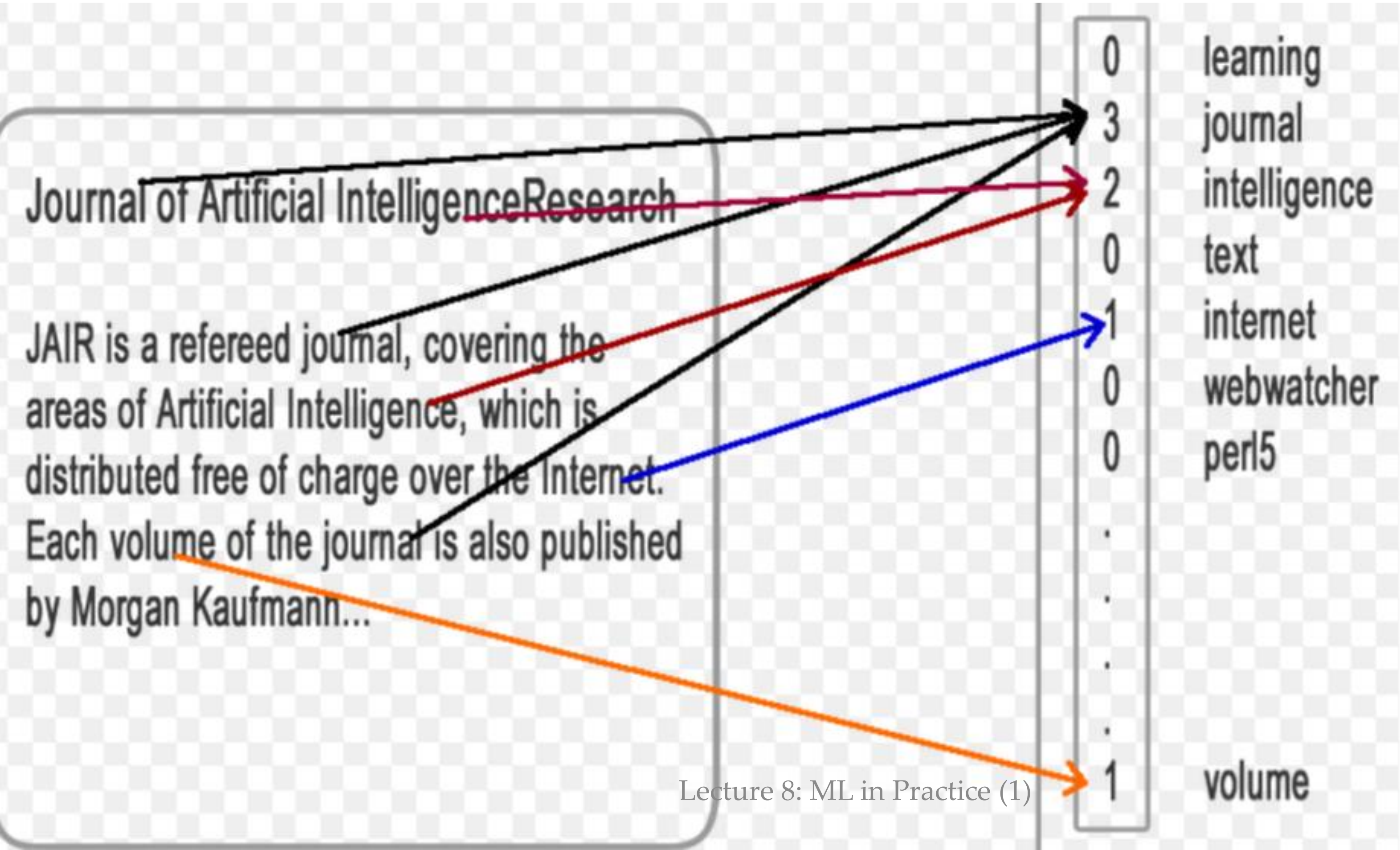
- The importance of features
- Unbalanced data, multiclass classification, teoretical model vs. real-world implementaton
- Evaluation:
  - How to assess what has been learned
  - Holdout estimation
  - Crossvalidation
  - Leave-one-out
  - Boostrap

The importance of good features

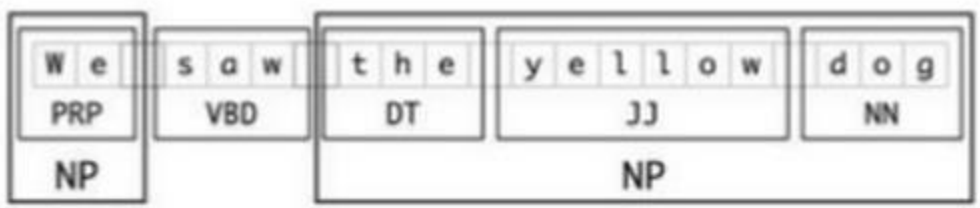
- Garbage in – garbage out

Bag of Words Representation





Parts Of Speech (PoS) representation



Segmentation and Labeling at both the Token and Chunk Levels

The Importance of Good Features

- Ex in Text Classification
  - BOW (Bag of words) (either counts or binary)
  - Phrases
  - n-Grams
  - Chunks
  - PoSs
  - PoS n-grams
  - etc.

ML success: Feature representation (aka feature engineering)

- The success of ML algorithms depens on how you present the data: you need great features that describe the structures inherent in your data:
  - Better features means flexibility
  - Better features means simpler models
  - Better features means better results

- However: The results you achieve are a factor of the model you choose, the data you have available and the features you prepared.

- That is, your results are dependent on many inter-dependent properties.

Feature Representation is a **knowledge representation** problem

- Transforming raw data into features that better represent the underlying problem to the predictive models, resulting in improved model accuracy on unseen data

- Question: what is the best representation of the sample data to learn a solution to your problem?

Practical Steps

[...] (tasks before here…)

- Select Data: Collect it together
- Preprocess Data: Format it, clean it, sample it so you can work with it.
- Transform Data: FEATURE REPRESENTATION happens here.
- Model Data: Create models, evaluate them and tune them.

[...] (tasks after here…)

Feature representation vs Feature Selection

- Feature representation is different from Attribute/Feature selection

Irrelevant and Reduntant Features

- Not all features have equal importance.

- Those attributes that are irrelevant to the problem need to be removed.

- Feature selection addresses those problems by automatically selecting a subset that are most useful to the problem.

Learning with unbalanced data

- Imbalanced data:
  - The number of positive examples is dwarfed by the number of negative examples (or viceversa)
- Solutions:
  - Assign an importance weight to the minority class
  - Subsampling
  - Oversampling

Multiclass Classification

- OVA (one versus all)
- AVA (all versus all)
- Binary tree

Theoretical Models vs Real Machine Learning Schemes

- For an algorithm to be useful in a wide range of real-world applications it must:
  - Allow missing values
  - Be robust in the presence of noise
  - Be able to approximate arbitrary concept descriptions
  - etc.

Evaluating what's been learned

- How predictive is the model we learned?
- Error on the training data is *not* a good indicator of performance on future data
  - Otherwise 1-NN would be the optimum classifier!
- Simple solution that can be used if lots of (labeled) data is available:
  - Split data into training and test set
- However: (labeled) data is usually limited
  - More sophisticated techniques need to be used

Issues in evaluation

- Statistical reliability of estimated differences in performance ($\rightarrow$ significance tests)
- Choice of performance measure:
  - Number of correct classifications
  - Accuracy of probability estimates
- Costs assigned to different types of errors
  - Many practical applications involve costs

Training and testing: empirical error

- Natural performance measure for classification problems: *error rate*
  - *Success*: instance's class is predicted correctly
  - *Error*: instance's class is predicted incorrectly
  - Error rate: proportion of errors made over the whole set of instances
- *Empirical (Resubstitution) error:* error rate obtained from training data
- *Empirical (Resubstitution)* error is (hopelessly) optimistic!

Training and testing: development/validation set & parameter tuning

- It is important that the test data is not used *in any way* to create the classifier
- Some learning schemes operate in two stages:
  - Stage 1: build the basic model
  - Stage 2: optimize parameter settings
- The test data can’t be used for parameter tuning!
- Proper procedure uses *three* sets: *training data*, *validation data*, and *test data*
  - Validation data is used to optimize parameters

Training and testing: test set

- *Test set*: independent instances that have played no part in formation of classifier
  - Assumption: both training data and test data are representative samples of the underlying problem

- Test and training data may differ in nature
  - Example: classifiers built using customer data from two different towns *A* and *B*
    - To estimate performance of classifier from town *A* in completely new town, test it on data from *B*

Making the most of the data

- Once evaluation is complete, *all the data* can be used to build the final classifier
- Generally, the larger the training data the better the classifier (but returns diminish)
- The larger the test data the more accurate the error estimate
- *Holdout* procedure: method of splitting original data into training and test set
  - Dilemma: ideally both training set *and* test set should be large!

Holdout estimation

- What to do if the amount of data is limited?
- The *holdout* method reserves a certain amount for testing and uses the remainder for training
  - Usually: one third for testing, the rest for training
- Problem: the samples might not be representative
  - Example: class might be missing in the test data
- Advanced version uses *stratification*
  - Ensures that each class is represented with approximately equal proportions in both subsets

Repeated holdout method

- Holdout estimate can be made more reliable by repeating the process with different subsamples
  - In each iteration, a certain proportion is randomly selected for training (possibly with stratificiation)
  - The error rates on the different iterations are averaged to yield an overall error rate
- This is called the *repeated holdout* method
- Still not optimum: the different test sets overlap
  - Can we prevent overlapping?

Cross-validation

- *Cross-validation* avoids overlapping test sets
  - First step: split data into *k* subsets of equal size
  - Second step: use each subset in turn for testing, the remainder for training
- Called *k-fold cross-validation*
- Often the subsets are stratified before the cross-validation is performed
- The error estimates are averaged to yield an overall error estimate

More on cross-validation

- Standard method for evaluation: stratified ten-fold cross-validation
- Why ten?
  - Extensive experiments have shown that this is the best choice to get an accurate estimate
  - There is also some theoretical evidence for this
- Stratification reduces the estimate's variance
- Even better: repeated stratified cross-validation
  - E.g. ten-fold cross-validation is repeated ten times and results are averaged (reduces the variance)

Leave-One-Out cross-validation

- Leave-One-Out:
  a particular form of cross-validation:
  - Set number of folds to number of training instances
  - I.e., for *n* training instances, build classifier *n* times
- Makes best use of the data
- Involves no random subsampling
- Very computationally expensive
  - (exception: NN)

Leave-One-Out-CV and stratification

- Disadvantage of Leave-One-Out-CV: stratification is not possible
  - It *guarantees* a non-stratified sample because there is only one instance in the test set!

The bootstrap

- CV uses sampling *without replacement*
  - The same instance, once selected, can not be selected again for a particular training/test set
- The *bootstrap* uses sampling *with replacement* to form the training set
  - Sample a dataset of *n* instances *n* times *with replacement* to form a new dataset of *n* ins
  - Use this data as the training set
  - Use the instances from the original dataset that don't occur in the new training set for testing

The 0.632 bootstrap

- Also called the *0.632 bootstrap*
  - A particular instance has a probability of 1–1/*n* of *not* being picked
  - Thus its probability of ending up in the test data is:

$$\left(1-\frac{1}{n}\right)^n \approx e^{-1} = 0.368$$

  - This means the training data will contain approximately 63.2% of the instances

Estimating error with the bootstrap

- The error estimate on the test data will be very pessimistic
  - Trained on just ~63% of the instances
- Therefore, combine it with the resubstitution/empirical error:

$$e = 0.632 \times e_{\text{test instances}} + 0.368 \times e_{\text{training instances}},$$

- The resubstitution/empirical error gets less weight than the error on the test data
- Repeat process several times with different replacement samples; average the results

More on the bootstrap

- Probably the best way of estimating performance for very small datasets
- However, it has some problems….

The end