

Processamento e Recuperação de Informação

Introduction

Supervised Learning

Text Classifiers

Other Issues

Processamento e Recuperação de Informação Classification

Departamento de Engenharia Informática Instituto Superior Técnico

1^o Semestre 2018/2019



Outline

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 - Nearest Neighbor Classifiers
 - Generative Bayesian Classifiers
 - Linear Discriminative Classifiers
 - Neural Networks
 - 4 Other Issues



Bibliography

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Organizing Knowledge

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- Organize into systematic knowledge structures
- Ontologies
 - Dewey Decimal System
 - ACM Computing Classification System
 - Patent Subject Classification
 - International Classification of Diseases
- Web catalogs
 - Yahoo Directory (RIP 2002–2014)
 - DMOZ Directory (RIP 1998–2017)
 - World Wide Web Virtual Library
 - Jasmine Directory



Organizing Knowledge

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Problem: Manual maintenance



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Supervised Learning

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Other Issues

Given a set of training data as input, use learning algorithm A to discover the function \hat{h} that minimizes the loss (e.g. the error over the set of training instances)

Input:
$$\{(x_i, y_i)\}_{i=1}^N$$
, $x_i \in \mathcal{R}^M$, $y_i \in \mathcal{R}$

Hypothesis space: $h^* \in H$

Loss function: L(h(x), y)

Learning Algorithm: $\hat{h} = A(\{(x_i, y_i)\}_{i=1}^N)$, such that

$$\hat{h} = \operatorname{argmin}_{h} \sum_{i=1}^{N} L(h(x_i), y_i)$$



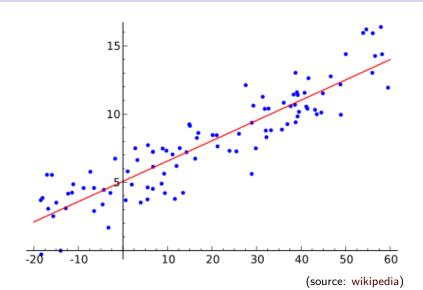
An Example: Linear Regression

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Linear Regression (cont.)

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Other Issues

• The hypothesis space:

$$h_{\vec{w}}(x) = w_0 + w_1 x$$

where $\vec{w} = [w_0, w_1]$

• The loss function:

$$L(h_{\vec{w}}, y) = \frac{1}{N} \sum_{i=1}^{N} (y_i - h_{\vec{w}}(x_i))^2$$

i.e. the sum of the squared error

We want to find

$$w^* = \underset{w}{\operatorname{argmin}} L(h_{\vec{w}}, y)$$



Minimizing the Loss

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- In simple cases, we can easily find one (or more) solution(s) to the problem of learning \hat{h}
 - For linear regression, take the derivatives and equal to 0
- In many cases this is not possible (or we may want to enforce some constraints on the parameters)
- In practice, there are many ways to estimate w^*



An Example: Gradient Descent

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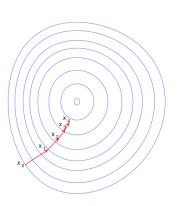
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Other Issues

 $w \leftarrow$ any point in the parameter space **loop** until convergence **do for each** w_i **in** \vec{w} **do** $w_i \leftarrow w_i - \alpha \frac{\partial}{\partial w_i} L(h_{\vec{w}}, y)$

 $\alpha = \text{learning rate}$



(source: wikipedia)



Classification

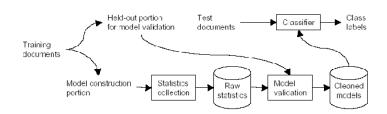
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- Learning to assign objects to classes given examples
- Learn a classifier (i.e., map the problem into supervised learning task)





An Example: Logistic Regression

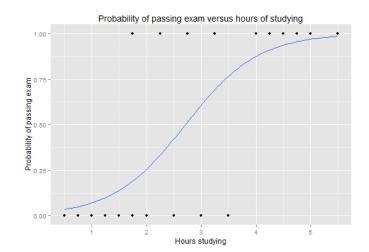
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(source: wikipedia)





Logistic Regression (cont.)

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The hypothesis space:

$$h_{\vec{w}}(x) = \frac{1}{1 + e^{-(w_0 + w_1 x)}}$$

where $\vec{w} = [w_0, w_1]$

• The loss function:

$$L(h_{\vec{w}}, y) = \frac{1}{N} \sum_{i=1}^{N} C(h_{\vec{w}}(x_i), y)$$

where

$$C(h_{\vec{w}}(x), y) = \begin{cases} -\log(h_{\vec{w}}(x)) & \text{if } y = 1\\ -\log(1 - h_{\vec{w}}(x)) & \text{if } y = 0 \end{cases}$$

We want to find

$$w^* = \underset{w}{\operatorname{argmin}} L(h_{\vec{w}}, y)$$



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Text Classification vs. Data Mining

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Other Issues

Leverage supervised learning together with method for representing textual information (e.g., VSM with TF-IDF)

- Lots of features and a lot of noise
- No fixed number of columns
- No categorical attribute values
- Data scarcity
- Larger number of class labels
- Hierarchical relationships between classes less systematic



Text Classifiers

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- Nearest Neighbor Classifiers
 - Classify documents according to the class distribution of their neighbors
- Generative Bayesian classifiers (e.g., naïve Bayes)
 - Discover the class distribution most likely to have generated a test document
- Linear discriminative classifiers (e.g., the perceptron, logistic regression, or support vector machines):
 - Discover an hyperplane that separates classes
- Neural networks
 - Discover a non-linear function, often resulting from a composition of many functions, that separates classes



Nearest Neighbor Classifiers

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Neural Networks

- Intuition: similar documents are expected to be assigned the same class label
 - Similarity: vector space model + cosine similarity
- Training:
 - Index each document and remember class label
- Testing:
 - Fetch k most similar documents to the given document
 - Majority class wins
 - Alternatives:
 - Weighted counts: counts of classes weighted by the corresponding similarity measure
 - Per-class offset: tuned by testing the classifier on a portion of training data held out for this purpose



kNN Classifier

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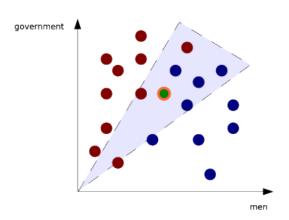
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$$score(c, d_q) = b_c + \sum_{d \in kNN(d_q)} sim(d_q, d)$$



Properties of kNN

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Other Issues

Advantages:

- Reuse of standard vector space model and availability of associated technology (e.g., inverted indexes)
- Collection updates are trivial
- Accuracy comparable to best known classifiers

Problems

- Classification efficiency
 - many lookups over the document collection/index
 - sorting by overall similarity
 - picking the best k documents
- Space overhead and redundancy
 - Data stored at level of individual documents
 - Poor generalization
- Choosing a value for k



Improvements for kNN

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- To reduce space requirements and speed up classification
 - Find clusters in the data and start by comparing instances against clusters (clustering covered in the next lecture)
 - Store only a few statistical parameters per cluster
 - In second step, compare with documents in only the most promising clusters
- However...
 - Ad-hoc choices for number and size of clusters and parameters
 - Number of clusters depends on the data



Bayesian Classifiers

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Other Issues

- Probabilistic document classifier
- Assumptions:
 - A document can belong to exactly one class
 - 2 Each class c has an associated prior probability P(c)
 - 3 There is a class-conditional document distribution P(d|c) for each class (i.e., the likelihood)
- Given a document d, the probability of it being generated by class c is:

$$P(c|d) = \frac{P(d|c)P(c)}{\sum_{\gamma} P(d|\gamma)P(\gamma)}$$

• The class with the highest probability is assigned to d_q (i.e., we use a maximum a-posteriory rule)



Learning the Document Distribution

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iveurar ivetwork

- P(d|c) is estimated based on parameters Θ
- ullet Θ are estimated based on two factors:
 - Prior knowledge before seeing any documents
 - 2 Terms in the training documents
- Bayes Optimal Classifier

$$P(c|d) = \int_{\Theta} \frac{P(d|c,\Theta)P(c|\Theta)}{\sum_{\gamma} P(d|\gamma,\Theta)P(\gamma|\Theta)} P(\Theta|D)$$

- This can be hard to compute
- Maximum Likelihood Estimate: $P(d|c, \hat{\Theta})$

$$\hat{\Theta} = argmax_{\Theta} P(d|c, \Theta)$$



Naïve Bayes Classifier

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Other Issues

Naïve assumption

- assumption of independence between terms
- joint term distribution is the product of the marginals
- Widely used owing to
 - simplicity and speed of training, applying, and updating
- Two kinds of widely used marginals for text
 - Binary model (Bernoulli)
 - Multinomial model



Naïve Bayes Models

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Other Issues

Binary Model: Each parameter $\theta_{c,t}$ indicates the probability that a document in class c will mention term t at least once

$$P(d|c,\Theta) = \prod_{t \in d} \theta_{c,t} \prod_{t \notin d} (1 - \theta_{c,t})$$
$$\theta_{c,t} = \frac{N_{c,t}}{N_c}$$

 $N_{c,t} = n$. of docs in class c containing term t $N_c = n$. of docs in class c



Naïve Bayes Models (cont.)

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Multinomial Model:

- \bullet each class has an associated die with |W| faces
- each parameter $\theta_{c,t}$ denotes probability of the face turning up on tossing the die, i.e. $\sum_{d \in c} n(d,t) / \sum_{d \in c} \ell_d$
- term t occurs n(d, t) times in document d
- document length is a random variable denoted L

$$P(d|c,\Theta) = P(L = \ell_d|c)P(d|\ell_d,c)$$

$$= P(L = \ell_d|c)\frac{\ell_d!}{\prod_{t \in d} n(d,t)!} \prod_{t \in d} \theta_{c,t}^{n(d,t)}$$

$$\sim P(L = \ell_d|c)\prod_{t \in d} \theta_{c,t}^{n(d,t)}$$



Parameter Smoothing

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Other Issues

• What if a test document d_q contains a term t that never occurred in any training document in class c?



Parameter Smoothing

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Other Issues

• What if a test document d_q contains a term t that never occurred in any training document in class c?

- $P(c|d_q) = 0$
- Even if many other terms clearly hint at a high likelihood of class c generating the document
- Thus, MLE cannot be used directly
- We can use Laplace smoothing
 - Simply adds 1 to each count

$$\theta_{c,t} = \frac{\sum_{d \in c} n(d,t) + 1}{\sum_{d \in c} \ell_d + |W|}$$



Performance Analysis

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- Multinomial naïve Bayes classifier generally outperforms the binary variant
- kNN may outperform Naïve Bayes
- Naïve Bayes is faster and more compact
- Determines decision boundaries
 - Regions of the term-space where different classes have similar probabilities
 - Documents in these regions are hard to classify
 - Strongly biased



Discriminative Classification

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- Naïve Bayes classifiers are generative
- Differently, discriminative classifiers:
 - Directly map the feature space to class labels
 - Class labels are encoded as numbers
 - ullet e.g: +1 and -1 for two a class problem
- For instance, we can try to find a vector α such that the sign of $\alpha \cdot d + b$ directly predicts the class of a document d
- Possible solutions:
 - Linear least-square regression
 - The Perceptron
 - Logistic Regression
 - Support Vector Machines



What is a Linear Discriminative Classifier?

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Essentially:

- Classification decision is based on the value of a linear combination of the features
- Can be seen as the splitting of a high-dimensional input space with a hyperplane

$$y(d_1,\ldots,d_n)=f(\alpha_1d_1+\alpha_2d_2+\ldots+\alpha_nd_n)$$

- α_i are parameters (i.e., the weight of each feature d_i)
- f is the activation function (e.g., $f(d) = 1_{x \ge 0}(d)$)
- The result of $y(d_1, \ldots, d_n)$ corresponds to the estimated class



The Bias Term

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- Notice that, according to the previous definition, the decision hyperplane must go through the origin
- Could be achieved by preprocessing the input, but this is not always desirable or possible
- Solution : Add a bias input:

$$y(d_1,\ldots,d_n)=f(b+\alpha_1d_1+\ldots+\alpha_nd_n)$$

- Same as an input connected to the constant 1
- We consider this ghost input implicit henceforth



Training: The Perceptron Algorithm

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Switching to vector notation:

$$y(\mathbf{d}) = f(\alpha \mathbf{d}) = f_{\alpha}(d) \tag{1}$$

 Assume we need to separate sets of points A (i.e., the positive examples) and B (i.e., the negative examples)

$$E(\alpha) = \sum_{\mathbf{d} \in A} (1 - f_{\alpha}(\mathbf{d})) + \sum_{\mathbf{d} \in B} f_{\alpha}(\mathbf{d})$$
 (2)

- Goal: $E(\alpha) = 0$
- ullet Start from a random lpha and improve it iteratively



Algorithm Pseudo-Code

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Other Issues

1 Start with random α , set t = 0

2 Select a vector $\mathbf{d} \in A \cup B$

3 If $\mathbf{d} \in A$ and $\alpha \mathbf{d} \leq 0$, then $\alpha_{t+1} = \alpha_t + \mathbf{d}$

4 Else if $\mathbf{d} \in B$ and $\alpha \mathbf{d} \geq 0$, then $\alpha_{t+1} = \alpha_t - \mathbf{d}$

Onditionally go to step 2

• Guaranteed to converge iff A and B are linearly separable!



Problems of Simple Perceptrons (1)

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Other Issues

Overfitting

- The standard Perceptron returns the most recent version of the weight vector
- Intuitively, this version is over-adapted to the last few instances, and may work less well for other instances
- The Averaged Perceptron returns the average of all versions (or the last few versions) of the weight vector
- An implementation trick involves setting a learning step that takes the averaging effect into account



Problems of Simple Perceptrons (2)

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Other Issues

Multi-class classification

- Several problems involve multi-class classification
- Multi-class classification can be made through one weight vector for each category, assigning instances to the class for which the model predicts a higher value
- In practice, we can represent this with one giant weight vector and repeated features for each category
- Update rule involves changing the weights for the true class and the class that was predicted
- Other options for update rule can be considered, e.g. updating classes with higher score than correct one



Summary of Simple/Averaged Perceptrons

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- Simple and reasonably efficient online training
- Easy to extend in order to consider multi-class classification (and also structured prediction)
- Works well for document classification, and more generally for problems with many features
- Limited capabilities (e.g., does not try to optimize the separation "distance" between classes)
 - Just looks for a hyperplane that separates the two sets
 - Methods such as Support Vector Machines, on the other hand, try to maximize the distance between two closest opposite sample points (i.e., the margin of the separating hyperplane)



Linear Discriminative Classifiers and SVMs

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Hypothesis:

- The classes can be separated by an hyperplane
- The hyperplane that is close to many training data points has a greater chance of misclassifying test instances
- An hyperplane that passes through a "no-man's land", has lower chances of misclassifications
- Make a decision by thresholding
 - Seek an hyperplane that maximizes the distance to any training point
 - Choose the class on the same side of the hyperplane as the test document (i.e., same as in the Perceptron)



Discovering the Hyperplane

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- \bullet Assume the training documents are separable by an hyperplane perpendicular to a vector α
- ullet Seek a vector α which maximizes the distance of any training point to the hyperplane
- This corresponds to solving the following quadratic programming problem:

Minimize
$$\frac{1}{2}\alpha \cdot \alpha$$

subject to $c_i(\alpha \cdot d_i + b) \ge 1, \forall i = 1, \dots, n$



SVM Classifier

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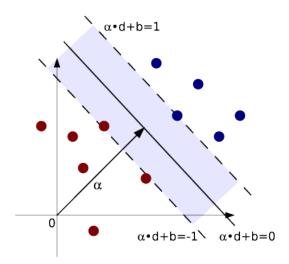
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Non Separable Classes

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Other Issues

Classes in the training data not always separable

We introduce slack variables

Minimize
$$\frac{1}{2}\alpha \cdot \alpha + C \sum_i \xi_i$$

subject to $c_i(\alpha \cdot d_i + b) \ge 1 - \xi_i, \forall i = 1, \dots, n$
and $\xi_i \ge 0, \forall i = 1, \dots, n$

Implementations often solve the equivalent dual problem

Maximize
$$\sum_{i} \lambda_{i} - \frac{1}{2} \sum_{i,j} \lambda_{i} \lambda_{j} c_{i} c_{j} (d_{i} \cdot d_{j})$$
 subject to $\sum_{i} c_{i} \lambda_{i} = 0$ and $0 < \lambda_{i} < C, \forall i = 1, ..., n$



Analysis of SVMs

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Complexity:

- Quadratic optimization problem
- Requires on-demand computation of inner-products
- Recent SVM packages work in linear time

Performance:

- Amongst most accurate classifier for text
- Better accuracy than Naïve Bayes and most classifiers
- Linear SVMs suffice
 - Standard text classification tasks have classes almost separable using a hyperplane in feature space
- Non-linear SVMs can be achieved through kernel functions



Neural Networks

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Other Issues (1)

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- Tokenization and feature extraction
 - E.g.: replacing monetary amounts by a special token, part-of-speech tagging, representations based on *n*-grams, etc.
- Handling scenarios with multiple classes, or with multiple labels per test document, with binary classifyers like SVMs
 - E.g., one-vs.-rest heuristic
 - e.g. "sports" vs. "not-sports", "science" vs. "not-science", etc.
 - Create a classifier for each case
 - Assign class(es) with the highest confidence



Other Issues (2)

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Evaluating text classifiers

- Accuracy
- Training speed and scalability
- Simplicity, speed, and scalability for document modifications
- Ease of diagnosis, interpretation of results, and adding human judgment and feedback
- Many other practical issues...



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Questions?