



Processamento
e Recuperação
de Informação

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Other Issues

Processamento e Recuperação de Informação

Classification

Departamento de Engenharia Informática
Instituto Superior Técnico

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2018/2019



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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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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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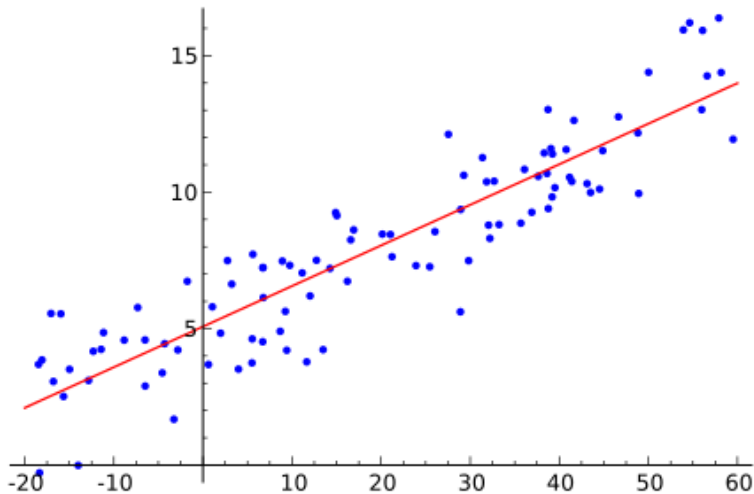
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(source: [wikipedia](#))



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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Other Issues

- 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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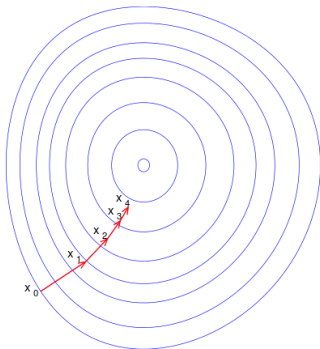
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Other Issues

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

α = learning rate



(source: [wikipedia](#))



Classification

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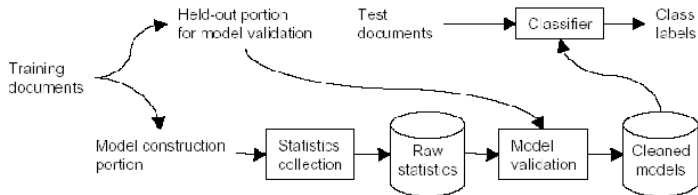
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Other Issues

- 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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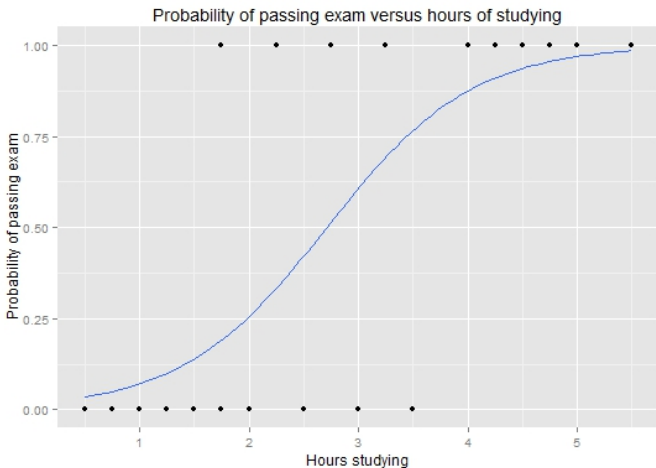
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(source: [wikipedia](#))



Logistic Regression (cont.)

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Other Issues

- 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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Other Issues

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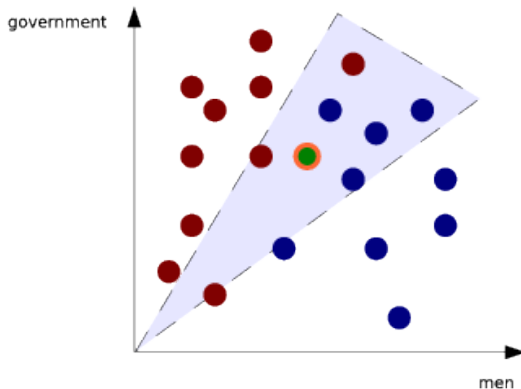
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$$\text{score}(c, d_q) = b_c + \sum_{d \in kNN(d_q)} \text{sim}(d_q, d)$$



Properties of k NN

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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 k NN

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Other Issues

- 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:
 - 1 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-posteriori* rule)



Learning the Document Distribution

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Other Issues

- $P(d|c)$ is estimated based on parameters Θ
- Θ are estimated based on two factors:
 - 1 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: $P(d|c, \hat{\Theta})$

$$\hat{\Theta} = \operatorname{argmax}_{\Theta} P(d|c, \Theta)$$



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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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:

- 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

$$\begin{aligned} P(d|c, \Theta) &= P(L = \ell_d | c) P(d | \ell_d, c) \\ &= P(L = \ell_d | c) \frac{\ell_d!}{\prod_{t \in d} n(d, t)!} \prod_{t \in d} \theta_{c,t}^{n(d,t)} \\ &\sim P(L = \ell_d | c) \prod_{t \in d} \theta_{c,t}^{n(d,t)} \end{aligned}$$



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 ?



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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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Other Issues

- Multinomial naïve Bayes classifier generally outperforms the binary variant
- k NN 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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Other Issues

- Naïve Bayes classifiers are **generative**
- Differently, **discriminative** classifiers:
 - Directly map the feature space to class labels
 - Class labels are encoded as numbers
 - 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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Other Issues

- 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

$$y(d_1, \dots, d_n) = f(\alpha_1 d_1 + \alpha_2 d_2 + \dots + \alpha_n d_n)$$

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



The Bias Term

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Other Issues

- 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:

$$y(d_1, \dots, d_n) = f(b + \alpha_1 d_1 + \dots + \alpha_n d_n)$$

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



Training : The Perceptron Algorithm

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Other Issues

- Switching to vector notation:

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

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

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

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



Algorithm Pseudo-Code

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- ➊ Start with random α , set $t = 0$
 - ➋ Select a vector $\mathbf{d} \in A \cup B$
 - ➌ If $\mathbf{d} \in A$ and $\alpha \mathbf{d} \leq 0$, then $\alpha_{t+1} = \alpha_t + \mathbf{d}$
 - ➍ Else if $\mathbf{d} \in B$ and $\alpha \mathbf{d} \geq 0$, then $\alpha_{t+1} = \alpha_t - \mathbf{d}$
 - ➎ Conditionally 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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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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Other Issues

- 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** between the classes)



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

$$\begin{array}{ll}\text{Minimize} & \frac{1}{2} \alpha \cdot \alpha \\ \text{subject to} & c_i(\alpha \cdot d_i + b) \geq 1, \forall i = 1, \dots, n\end{array}$$



SVM Classifier

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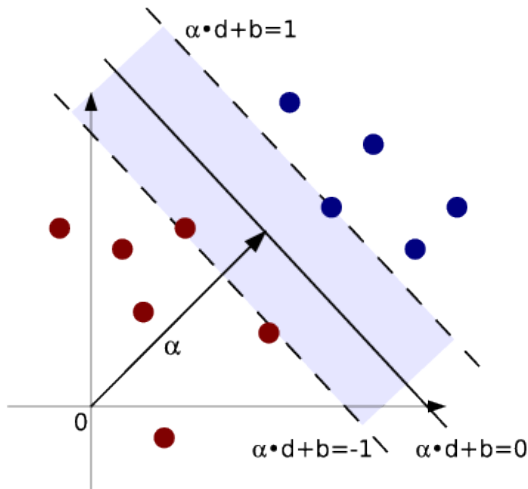
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Non Separable Classes

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Other Issues

- Classes in the training data not always separable
- We introduce **slack variables**

$$\begin{aligned} &\text{Minimize} && \frac{1}{2}\alpha \cdot \alpha + C \sum_i \xi_i \\ &\text{subject to} && c_i(\alpha \cdot d_i + b) \geq 1 - \xi_i, \forall i = 1, \dots, n \\ &&& \text{and } \xi_i \geq 0, \forall i = 1, \dots, n \end{aligned}$$

- Implementations often solve the equivalent dual problem

$$\begin{aligned} &\text{Maximize} && \sum_i \lambda_i - \frac{1}{2} \sum_{i,j} \lambda_i \lambda_j c_i c_j (d_i \cdot d_j) \\ &\text{subject to} && \sum_i c_i \lambda_i = 0 \\ &&& \text{and } 0 \leq \lambda_i \leq C, \forall i = 1, \dots, n \end{aligned}$$



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**



Logistic Regression as a Linear Classifier

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Recall that for logistic regression, we have that:

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

We would predict positive if $P(Y = 1|X) > P(Y = 0|X)$, or equivalently:

$$\frac{P(Y=1|X)}{P(Y=0|X)} > 1$$

Taking logs on both sides:

$$\log \left(\frac{P(Y=1|X)}{P(Y=0|X)} \right) > 0$$

Thus, we see that the decision boundary is given by the plane $w_0 + \sum_i w_i X_i$ (similarly to the Perceptron or SVM classifiers).



Neural Networks

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Measures of Accuracy

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Two cases:

- 1 Each document is associated with exactly **one class**, or
- 2 Each document is associated with a **subset of classes** (also referred to as multi-label classification)



Single-class Scenario

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- For the first case, we can use a **confusion matrix** M
 - $M[i, j]$ is the number of test documents belonging to class i which were assigned to class j
 - Perfect classifier: diagonal elements $M[i, i]$ would be nonzero
 - Example:

$$M = \left\{ \begin{array}{c|c|c} 5 & 0 & 0 \\ \hline 1 & 3 & 0 \\ \hline 1 & 2 & 4 \end{array} \right\}$$

- If M is large, we use

$$\text{accuracy} = \sum_i M[i, i] / \sum_{i,j} M[i, j]$$



Multiple-class Scenario

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Other Issues

- One-vs.-rest
 - Create a two-class problem for every class
 - E.g. “sports” and “not-sports”, “science” and “not-science”, etc.
 - We have a classifier for each case
- Quality is measured by **recall** and **precision**
 - Let C_d be the correct classes for document d and C'_d be the set of classes estimated by the classifier

$$precision = \frac{C'_d \cap C_d}{C'_d}$$

$$recall = \frac{C'_d \cap C_d}{C_d}$$



Micro-Averaged Precision (Single Class)

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In a problem with n classes, let C_i be the number of documents in class i and let C'_i be the number of documents estimated to be of class i by the classifier

- **Micro-averaged precision** is defined as

$$\frac{\sum_{i=1}^n C'_i \cap C_i}{\sum_{i=1}^n C'_i}$$

- **Micro-averaged recall** is defined as

$$\frac{\sum_{i=1}^n C'_i \cap C_i}{\sum_{i=1}^n C_i}$$

- Micro-averaged precision/recall measures correctly classified documents, thus favoring large classes



Macro-Averaged Precision (Single Class)

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In a problem with n classes, let P_i and R_i be the precision and recall, respectively, achieved by a classifier for class i

- **Macro-averaged precision** is defined as

$$\frac{1}{n} \sum_{i=1}^n P_i$$

- **Macro-averaged recall** is defined as

$$\frac{1}{n} \sum_{i=1}^n R_i$$

- Macro-averaged precision/recall measures performance per class, giving all classes equal importance



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Other Issues (1)

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Other Issues

- Tokenization and feature extraction
 - E.g.: replacing monetary amounts and other numeric quantities by a special token, part-of-speech tagging, representations based on n -grams, etc.
- Evaluating text classifiers in practice
 - 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?