#### LINEAR CLASSIFIERS

Classifiers

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### Motivation

- Simple and popular **supervised** models
- Suitable for regression and classification (we'll study regression later)
- Linear models inspired a lot of other methods like Neural Networks and Support Vector Machines.

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#### Representation space: attributes as coordinates



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Separate oranges from red and green apples using a **linear** frontier in the attribute space



Illustrations: Jason Mayes Machine Learning 101

#### Multi-class linear classifier



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#### Supervised classification



#### Linear separators

How can we find the separating hyperplane ?  $w_i$ 

Many approaches:

- MSE (linear regression, studied later)
- LDA linear discriminant analysis
- Logistic Regression (a classification method)
- Perceptron (studied later)
- Support Vector Machines (studied later)

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## Linear Discriminant Analysis Fischer, 1936



#### Finding the direction maximizing a ratio of "between-class variance" to "within-class variance"

Figure: Cheng Yen Li, 2014

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## Linear Discriminant Analysis

- Can be generalized for any number of classes
- Similar to PCA, rely on the eigen-decomposition of covariance matrices, leading to high complexity  $O(n^3)$

### Logistic Regression

... should be called Logistic Discrimination

Basic assumption: the difference between the logarithms of the class-conditional density functions is linear in the variables x:

$$\log\left(\frac{p(\boldsymbol{x}|\omega_1)}{p(\boldsymbol{x}|\omega_2)}\right) = \beta_0 + \boldsymbol{\beta}^T \boldsymbol{x}$$

where  $\omega_1$ ,  $\omega_2$  are the classes

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### Logistic Regression

The previous equation can be rewritten as

$$p(\omega_2 | \mathbf{x}) = \frac{1}{1 + \exp(\beta'_0 + \boldsymbol{\beta}^T \mathbf{x})}$$
$$p(\omega_1 | \mathbf{x}) = \frac{\exp(\beta'_0 + \boldsymbol{\beta}^T \mathbf{x})}{1 + \exp(\beta'_0 + \boldsymbol{\beta}^T \mathbf{x})}$$

(easy to generalize to arbitrary number of classes)

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# Logistic Regression Decision between two classes assign $\mathbf{x}$ to $\begin{cases} \omega_1 & \text{if } \frac{p(\omega_1 | \mathbf{x})}{p(\omega_2 | \mathbf{x})} \end{cases} < 1$ which leads to assign $\mathbf{x}$ to $\begin{cases} \omega_1 \\ \omega_2 \end{cases}$ if $\beta'_0 + \beta^T \mathbf{x} \begin{cases} > \\ < 0 \end{cases}$ Again, a linear model.

#### Logistic Regression

Maximum Likelihood

For C classes, the likelihood of the examples is

$$L = \prod_{i=1}^{C} \prod_{r=1}^{n_i} p(\boldsymbol{x}_{ir} | \omega_i)$$

Maximizing L is equivalent to maximize L'  $\log(L') = \sum_{s=1}^{C} \sum_{r=1}^{n_s} \log(p(\omega_s | \mathbf{x}_{sr}))$ 

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## Linear separability ?

#### Solutions:

- Add or generate attributes
- Use non-linear models



## Conclusion

• Linear models are easy to build and interpret

 Logistic regression is especially popular because it offer good performances and its outputs are interpretable as probabilities.

#### References

#### Books

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- Andrew Webb, K. Copsey. Statistical Pattern Recognition 3rd Edition. Wiley, 2011.

#### **Tutorials**

- R. Shaw. Logistic Regression: A Concise Technical Overview.
  <u>https://www.kdnuggets.com/2018/02/logistic-regression-concise-technical-overview.html</u>
- Cheng Li, Bingyu Wang Fisher Linear Discriminant Analysis, 2014 <u>https://www.semanticscholar.org/paper/Fisher-Linear-Discriminant-Analysis-Li/1ab8ea71fbef3b55b69e142897fadf43b3269463</u>
- Scikit-learn:
  - Generalized Linear Models <u>https://scikit-learn.org/stable/modules/linear\_model.html</u>
  - <u>https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LogisticRegression.html</u>
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