7: Catchup Session & very short intro to Other Classifiers

Non-examinable

Machine Learning and Real-world Data (MLRD)

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What happens in a catchup session?

- Lecture and practical session as normal
- New material in lecture is non-examinable
- Main purpose: catch up on all ticks in segment
- You can also attempt some starred ticks.
- Demonstrators help as per usual.

Naive Bayes is a probabilistic classifier

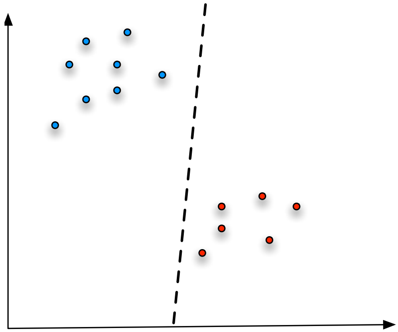
- Given a set of input features a probabilistic classifier provide a distribution over classes.
- That is, for a set of observed features O and classes $c_1 ... c_n \in C$ gives $P(c_i|O)$ for all $c_i \in C$
- For us O was the set all the words in a review $\{w_1, w_2, ..., w_n\}$ where w_i is the ith word in a review, $C = \{\text{POS}, \text{NEG}\}$
- We decided on a single class by choosing the one with the highest probability given the features:

$$\hat{c} = \operatorname*{argmax}_{c \in C} P(c|O)$$

An SVM is a popular discriminative classifier

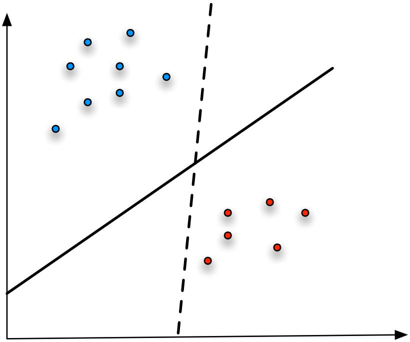
- A Support Vector Machine (SVM) is a non-probabilistic binary linear classifier
- SVMs assign new examples to one category or the other
- SVMs can reduce the amount of labeled data required to gain good accuracy
- SVMs can be efficiently adapted to perform a non-linear classification

SVMs find hyper-planes that separate classes



- Our classes exist in a multidimensional feature space
- A linear classifier will separate the points with a hyper-plane

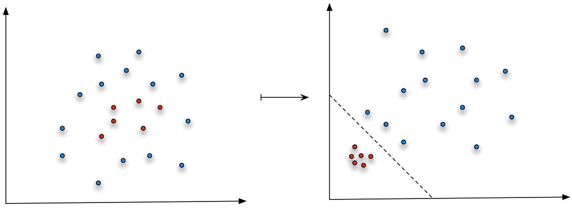
SVMs find a maximum-margin hyper-plane in noisy data



- There are many possible hyper-planes
- SVMs find the best hyper-plane such that the distance from it to the nearest data point from each class is maximised
- i.e. the hyper-plane that passes through the widest possible gap (hopefully helps to avoid over-fitting)

SVMs can be very efficient and effective

- Efficient when learning from a large number of features (good for text)
- Effective even with relatively small amounts of labelled data (we only need points close to the plane to calculate it)
- We can choose how many points to involve (size of margin) when calculating the plane (tuning vs. over-fitting)
- Can separate non-linear boundaries by changing the feature space (using a kernal function)



Choice of classifier will depend on the task

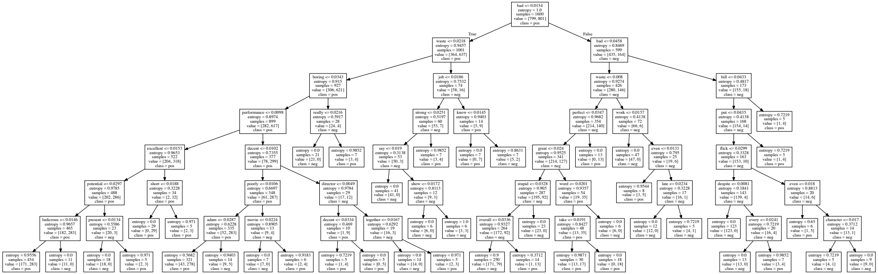
Comparison of a SVM and Naive Bayes on the same task:

- 2000 imdb movie reviews, 1600/400 test/training split
- preprocess with improved tokeniser (lowercased, removed uninformative words, dealt with punctuation, lemmatised words)

	SVM	**Naive Bayes**
Accuracy on train	0.98	0.96
Accuracy on test	0.84	0.80

- But from Naive Bayes I know that *character*, *good*, *story*, *great*, ... are informative features
- SVMs are more difficult to interpret

Decision tree can be used to visually represent classifications



- Simple to interpret
- Can mix numerical and categorical data
- You specify the parameters of the tree (maximum depth, number of items at leaf nodes—both change accuracy)
- But finding the optimal decision tree can be NP-complete

Information gain can be used to decide how to split

- Information gain is defined in terms of entropy H

Entropy of tree node:

$$H(n) = -\sum_{p} p_i \log_2 p_i$$

where p_i are the probabilities of each class at node n

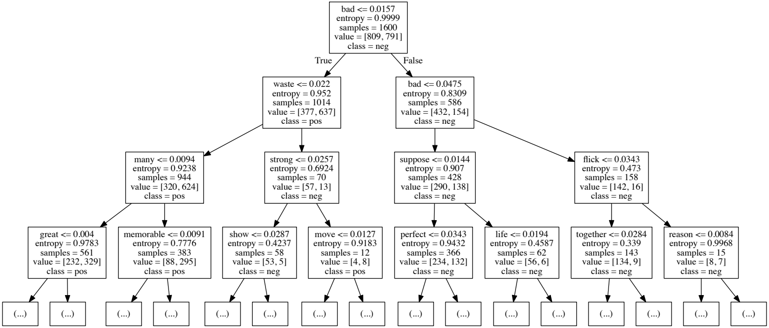
- Information gain I is the reduction in entropy of n achieved by learning the state of the random variable D.

Information gain:

$$I(n, D) = H(n) - H(n|D)$$

where $H(n|D)$ is the weighted entropy of the daughter nodes if we split on D.

Information gain can be used to decide how to split



Results on the movie review dataset:

	SVM	**Naive Bayes**	**DTree** (max depth 7)
Accuracy on train	0.98	0.96	0.80
Accuracy on test	0.84	0.80	0.69

Feed-forward Neural Networks

Think about multi-class classification:

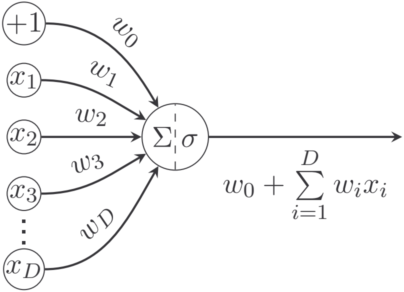
- D – number of features (input)
- K – number of classes (output)
- $\mathbf{x}$ – the input feature vector

Think about a particular class, say y_k. We describe the "friendship" between $\mathbf{x}$ and y_k in the following way:

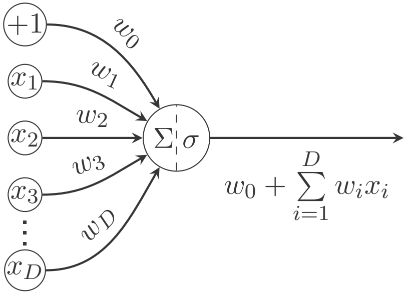
$$\text{score\_function}(x, y_k) = w_0 + \sum_{i=1}^{D} w_i x_i$$

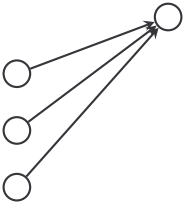
where $\mathbf{w}$ measures how much each feature w_i contributes to y_k.

Feed-forward Neural Networks



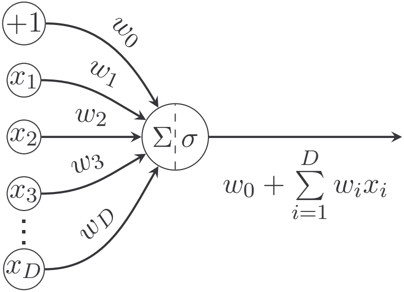
Feed-forward Neural Networks

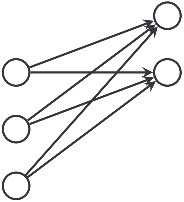




For each class y_k, we do the same thing.

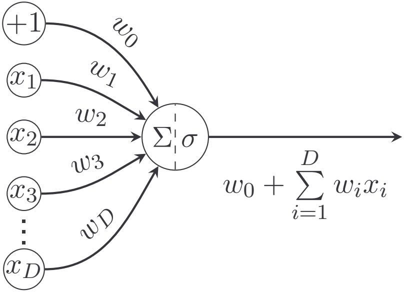
Feed-forward Neural Networks

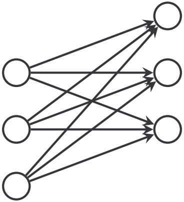




For each class y_k, we do the same thing. **Again**

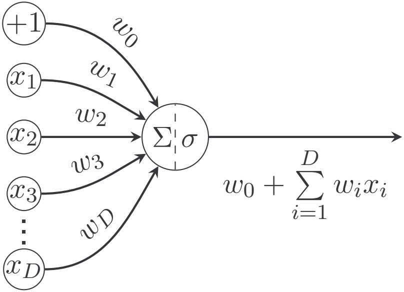
Feed-forward Neural Networks

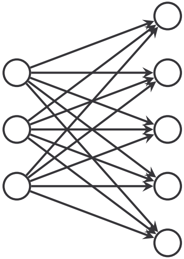




For each class y_k, we do the same thing. Again **and again**

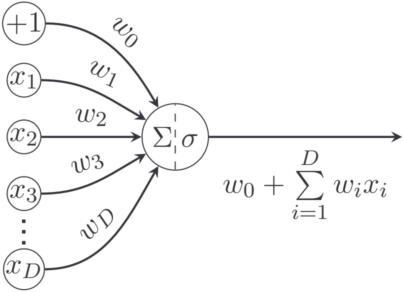
Feed-forward Neural Networks

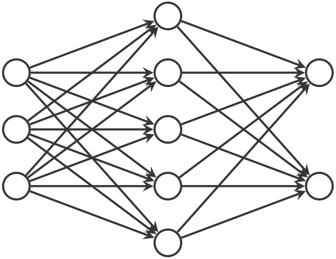




For each class y_k, we do the same thing. Again and again **and again. This is called perceptron, which was invented by Frank Rosenblatt in 1958.**

Feed-forward Neural Networks





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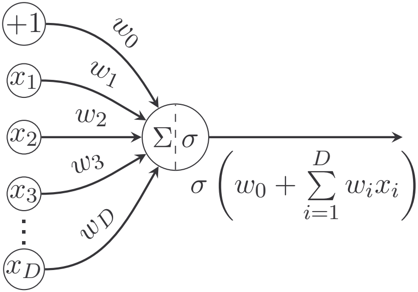
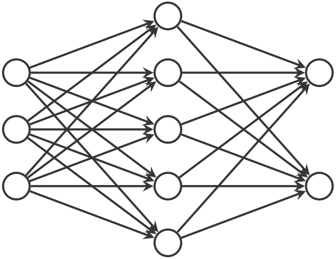
Feed-forward Neural Networks





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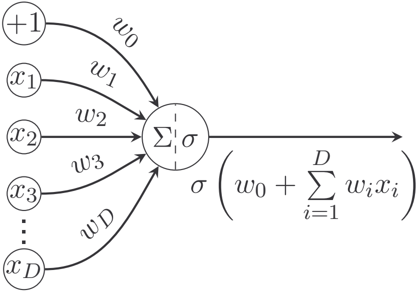
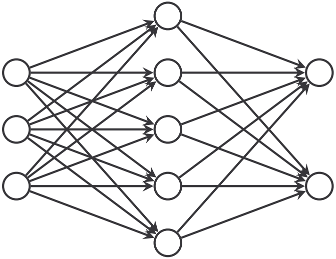
Sigmoid $\sigma(x) = \frac{1}{1+e^{-x}}$

Otherwise, simple matrix multiplication.

Feed-forward Neural Networks





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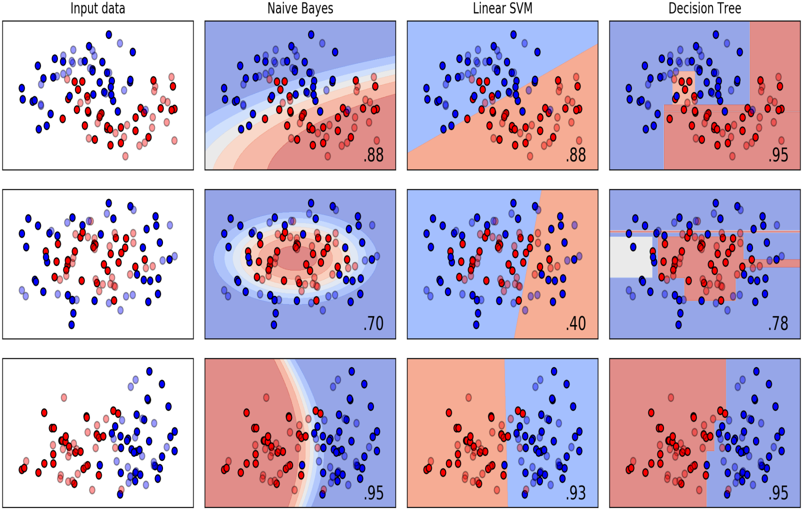
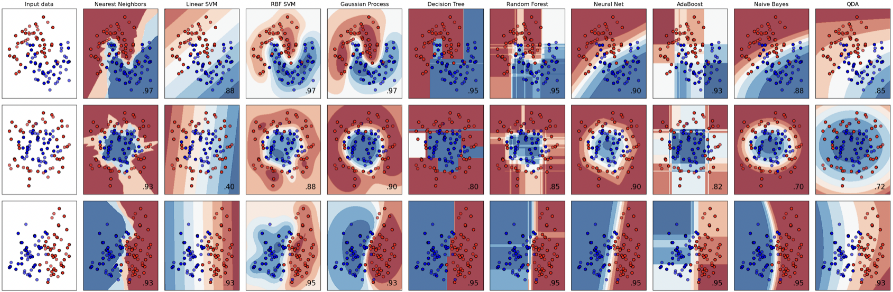
Sigmoid $\sigma(x) = \frac{1}{1+e^{-x}}$
Otherwise, simple matrix multiplication. **Now you can do non-linear classification.**

Nature of decision Boundaries: artificial data



Modified from SciKit Learn Classifier Comparison

More classifiers



https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html

Training data points: dark
Test data points: light

End of Classification Topic

- Next topic on Friday
- Hidden Markov Models
- Lecturer: Andreas Vlachos