Machine Learning for Language Processing (L101)

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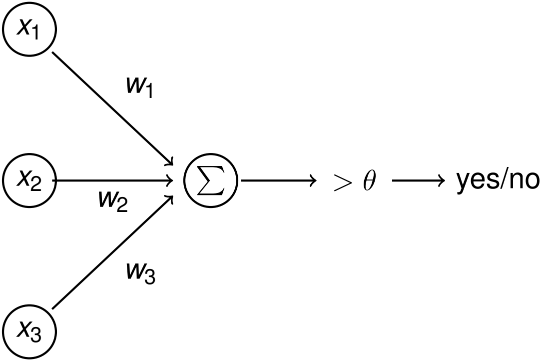
Outline of today's lecture

Perceptron algorithm

Kernels

Interpreting English compound nouns using kernel methods

Perceptron



Dot product of an input vector $\vec{x}$ and a weight vector $\vec{w}$, compared to a threshold θ

Perceptron

- The perceptron was one of the first neural network architectures (Rosenblatt 1962)
- Cognitively inspired — but nobody knew much about how real neurons worked then ...
- Multilayer perceptron is not a perceptron ...
- perceptron algorithm for learning — suitable for classification where linearly separable.
- Many variants: kernel perceptron, voted perceptron (which is competitive with techniques such as SVMs).
- In NLP, mainly for parse selection (alternative to MaxEnt).
- Description here based on Manning and Schütze: see Stephen Clark's notes for perceptron applied to tagging.

Perceptron learning algorithm

- Simple example of gradient descent (also know as hill climbing, gradient ascent).
- Move the prediction in the direction of the training data via the steepest gradient (i.e., derivative).
- Theory fairly complex, implementation simple (and fast!).
- Will converge if problem is linearly separable, but:
  - boundary may flip back and forth — not always clear in training if it will converge or if problem non-linear
  - results depend on training data order, boundaries non-optimal

Perceptron learning algorithm

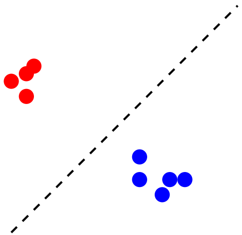
θ threshold, $\vec{w}$ weights, $\vec{x}_j$ (numerical) feature vector

decision($\vec{x}_j, \vec{w}, \theta$) is **yes** if $\vec{w} \cdot \vec{x}_j > \theta$ else **no**

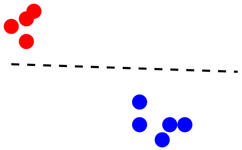
initialize $\vec{w}$ and θ to 0

while not converged **do**
  for each element $\vec{x}_j$ in training set **do**
    d := decision($\vec{x}_j, \vec{w}, \theta$)
    if trueclass($\vec{x}_j$) $= d$ **then continue**
    elseif trueclass($\vec{x}_j$) $=$ **yes then** $\theta := \theta - 1$
      $\vec{w} := \vec{w} + \vec{x}_j$
    elseif trueclass($\vec{x}_j$) $=$ **no then** $\theta := \theta + 1$
      $\vec{w} := \vec{w} - \vec{x}_j$
    fi

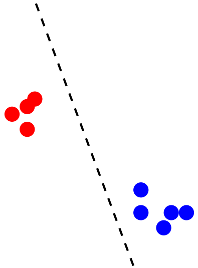
Perceptron boundaries



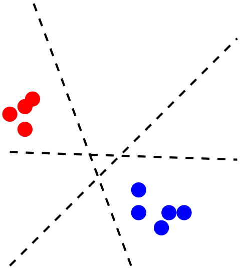
Perceptron boundaries



Perceptron boundaries



Perceptron boundaries



Perceptrons in NLP

- Introduced to NLP by Collins in 2002 (voted perceptron).
- Tagging, named entity recognition but primarily used for parse ranking.
- Can be used in conjunction with kernels. e.g., parse ranking: features are all subtrees of parse tree (so exponential number): use tree kernels.
- Kernels allow perceptrons and other methods to be used for problems that are not linerally separable.

Kernel methods

- Roughly: a kernel is a function which allows features to be mapped to an inner product in a higher-dimensional (possibly infinite) feature space.
- A valid kernel is defined by any symmetric finitely positive semi-definite function (psd).
- Hence, if we prove a function has these properties, then we have a kernel: no need to explicitly represent the mapping.
- Various similarity measurements are kernels, including cosine similarity and Jensen-Shannon divergence.

Why kernel methods?

- Allow structured objects (trees, strings, sets etc) to be classified by vectorial methods.
- Allow linear classifiers to learn non-linear classification functions.
- Multiple kernels may be combined to give a new kernel: usually better performance than treating them individually.
- Can be used in conjunction with a variety of ML methods: e.g., perceptron (first used by Aizerman et al 1964).
- SVMs use kernels.

Compound noun relations

- *cheese knife*: knife for cutting cheese
- *steel knife*: knife made of steel
- *kitchen knife*: knife characteristically used in the kitchen

Very limited syntactic/phonological cues in English, so assume parser gives: N1(x), N2(y), compound(x,y).

Language-specific restrictions

German compounds with non-compound translations:

Arzttermin	*doctor appointment	doctor's appointment
Terminvorschlag	* date proposal	proposed date
Terminvereinbarung	* date arrangement	arrangement of a date
Januarhälfte	* January half	half of January
Frühlingsanfang	* spring beginning	beginning of spring

Data-driven approaches to compound relation learning

- Find paraphrases by looking for explicit relationships in corpora: e.g., knife made of steel
  (Lauer: prepositions, Lapata: verbal compounds)
- treat as a supervised classification problem:
  1. human annotation of compounds: e.g., steel knife annotated with BE
  2. use distributional techniques to compare unseen to seen examples.

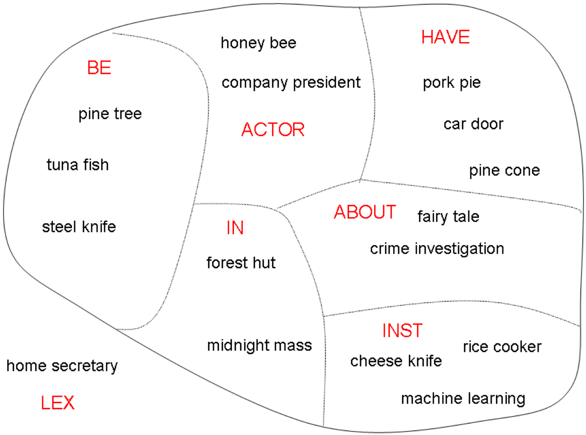
  Girju et al, Turner, Ó Séaghdha (2008) among others.

Relation schemes for learning experiments: Ó Séaghdha (2007)

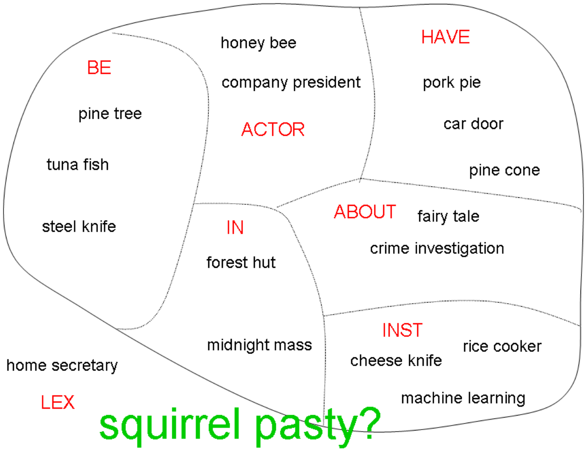
BE, HAVE, INST, ACTOR, IN, ABOUT: (with subclasses)
LEX: lexicalised, REL: weird, MISTAG: not a noun compound.

- Relation scheme based on Levi (1978)
- Considerable experimentation to define a usable scheme: some classes very rare (therefore not annotated reliably).
- Annotation of 1400 examples from BNC by two trained annotators, using extensive guidelines.
- Reasonable interannotator agreement (IAA).

Compound noun relation learning



Compound noun relation learning



Squirrels and pasties

Compound noun relation learning: Ó Séaghdha, 2008

- Use distributional methods: count vectors, acquired from subset of parsed British National Corpus and from Google 5-gram corpus.
- Distributions normalised to give probabilities.
- Apply distributional similarity to the compound phrase (note difference between compound noun and adjective-noun combination).
- Treating compounds as single words?
  Distributional vector for pork pie compared with vector for squirrel pasty?

Compound noun relation learning: Ó Séaghdha, 2008

- Two similarity methods that do work:
  1. Constituent similarity: compounds x1 x2 and y1 y2, compare x1 vs y1 and x2 vs y2.
     squirrel vs pork, pasty vs pie
  2. Relational similarity: compare **sentences** with x1 and x2 vs sentences with y1 and y2.
     squirrel is very tasty, especially in a pasty vs
     pies are filled with tasty pork
- Comparison using kernel methods: including combined constituent and relational similarity kernels.
- Best accuracy: about 65% (only slightly lower than agreement between annotators).
- Same system successfully used for a SEMEVAL task: classifying relationships between unconnected words in a sentence.

Kernel methods vs deep learning

- Deep learning is now potentially an alternative to kernels for structured input.
- Deep learning is theoretically more interesting (because less feature engineering, learn structure) but sometimes very difficult to apply to NLP problems.
- Kernel methods can be fast: Ó Séaghdha's linear kernels took 45 minutes to train on Google 5-gram with a slow CPU.
- Various hybrid methods are being proposed.