Classification & Clustering

CS6200
Information Retrieval
Spam
Spam
To: ...
From: ...
Subject: non profit debt
X-Spam-Checked: This message probably not SPAM
X-Spam-Score: 3.853, Required: 5
X-Spam-Level: *** (3.853)
X-Spam-Tests: BAYES_50,DATE_IN_FUTURE_06_12,URIBL_BLACK
X-Spam-Report-rig: ---- Start SpamAssassin (v2.6xx-cscf) results
   2.0 URIBL_BLACK Contains an URL listed in the URIBL blacklist
       [URLs: bad-debtyh.net.cn]
   1.9 DATE_IN_FUTURE_06_12 Date: is 6 to 12 hours after Received: date
   0.0 BAYES_50 BODY: Bayesian spam probability is 40 to 60%
       [score: 0.4857]

Say good bye to debt
Acceptable Unsecured Debt includes All Major Credit Cards, No-collateral
Bank Loans, Personal Loans,
Medical Bills etc.
http://www.bad-debtyh.net.cn
Spam

Website:

BETTING NFL FOOTBALL PRO FOOTBALL SPORTSBOOKS NFL FOOTBALL LINE ONLINE NFL SPORTSBKOS NFL
Players Super Book

When It Comes To Secure NFL Betting And Finding The Best Football Lines Players Super Book Is The Best Option! Sign Up And Ask For 30 % In Bonuses.

MVP Sportsbook

Football Betting Has Never been so easy and secure! MVP Sportsbook has all the NFL odds you are looking for. Sign Up Now and ask for up to 30 % in Cash bonuses.

Term spam:

pro football sportsbooks nfl football line online nfl sportsbooks nfl football gambling odds online pro nfl betting pro nfl gambling online nfl football spreads offshore football gambling online nfl gambling spreads online football gambling line online nfl betting nfl sportsbook online online nfl betting spreads betting nfl football online offshore gambling online gambling football online nfl football betting odds offshore football sportsbook online nfl football gambling ...

Link spam:

2,994 Reviews

Average Customer Review

Most Helpful Customer Reviews

2,142 of 2,353 people found the following review helpful

🌟🌟🌟🌟 Unexpected Direction, but Perfection (Potential spoilers, but pretty vague), August 24, 2010

By A. R. Bovey - See all my reviews

Amazon Verified Purchase (What's this?)

This review is from: Mockingjay (The Hunger Games, Book 3) (Hardcover)

This was a brilliant conclusion to the trilogy. I can only compare it to "Ender's Game" - and that is extremely high praise, indeed.

When I first closed the book last night, I felt shattered, empty, and drained.
2,994 Reviews

5 star: (1,204)
4 star: (521)
3 star: (480)
2 star: (406)
1 star: (383)

Average Customer Review

🌟🌟🌟🌟 (2,994 customer reviews)

Most Helpful Customer Reviews

2,142 of 2,353 people found the following review helpful

🌟🌟🌟🌟 Unexpected Direction, but Perfection (Potential spoilers, but pretty vague), August 24, 2010

By A. R. Bovey - See all my reviews

Amazon Verified Purchase (What's this?)

This review is from: Mockingjay (The Hunger Games, Book 3) (Hardcover)

This was a brilliant conclusion to the trilogy. I can only compare it to "Ender's Game" - and that is extremely high praise, indeed.

When I first closed the book last night, I felt shattered, empty, and drained.

Maybe not so good if found in a camera review
Sentiment

All user reviews

General Comments (148 comments)  82% positive
Ease of Use (108 comments)       78% positive
Screen (92 comments)             97% positive
Software (78 comments)           35% positive
Sound Quality (59 comments)      89% positive
Size (59 comments)               76% positive
Advertising

• Search engines sell customer clicks from
  • Sponsored search
  • Content match
• Just retrieve ads topically like other docs?
  • Ads are very short and targeted
• Build specialized classifiers
Advertising

Aquariums

Fish

Rainbow Fish Resources

Web Page

Supplies

Discount Tropical Fish Food
Feed your tropical fish a gourmet diet for just pennies a day!
www.cheapfishfood.com

Ad
Advertising

Example of semantic clustering to mitigate sparse term matches.
Chin, Ann

I work in the photo department at Scientific American magazine and I'm requesting your headshots for your upcoming article. We need high resolution color photos that an artist can use as reference to turn your headshot into an illustration. An ideal shot would be from the shoulder up without hats or anything distracting your face. If the owner of the photograph requires a reference credit, please let us know (Please note that the actual photo will not be published.)

Can you please send your headshots by Wednesday, April 18?

Thanks,
Annie
I don't have a *Scientific American* article coming out.
Classification

• Mapping from inputs to a finite output space
  • Contrast: regression and ranking
• Usually evaluated by accuracy
• Evaluated precision and recall if classes are very asymmetric in numbers or costliness (e.g., spam)
• Example: Naive Bayes
  • Simple, effective, similar to BM25
• Lots more: see book for SVM, nearest-neighbor
Axioms of Probability

• Define event space \( \bigcup_i F_i = \Omega \)

• Probability function, s.t. \( P : \mathcal{F} \rightarrow [0, 1] \)

• Disjoint events sum \( A \cap B = \emptyset \Leftrightarrow P(A \cup B) = P(A) + P(B) \)

• All events sum to one \( P(\Omega) = 1 \)

• Show that: \( P(\bar{A}) = 1 - P(A) \)
Conditional Probability

\[ P(A \mid B) = \frac{P(A, B)}{P(B)} \]

\[ P(A, B) = P(B)P(A \mid B) = P(A)P(B \mid A) \]

\[ P(A_1, A_2, \ldots, A_n) = P(A_1)P(A_2 \mid A_1)P(A_3 \mid A_1, A_2) \cdot \cdot \cdot P(A_n \mid A_1, \ldots, A_{n-1}) \]

*Chain rule*
Independence

\[ P(A, B) = P(A)P(B) \]
\[ \iff \]
\[ P(A \mid B) = P(A) \quad \land \quad P(B \mid A) = P(B) \]

In coding terms, knowing \( B \) doesn’t help in decoding \( A \), and vice versa.
Movie Reviews
there's some movies i enjoy even though i know i probably shouldn't and have a difficult time trying to explain why i did. "lucky numbers" is a perfect example of this because it's such a blatant rip-off of "fargo" and every movie based on an elmore leonard novel and yet it somehow still works for me. i know i'm in the minority here but let me explain. the film takes place in harrisburg, pa in 1988 during an unseasonably warm winter.
there's some movies i enjoy even though i know i probably shouldn't and have a difficult time trying to explain why i did. "lucky numbers" is a perfect example of this because it's such a blatant rip-off of "fargo" and every movie based on an elmore leonard novel and yet it somehow still works for me. i know i'm in the minority here but let me explain. the film takes place in harrisburg, pa in 1988 during an unseasonably warm winter."
there's some movies i enjoy even though i know i probably shouldn't and have a difficult time trying to explain why i did. "lucky numbers" is a perfect example of this because it's such a blatant rip-off of "fargo" and every movie based on an elmore leonard novel and yet it somehow still works for me. i know i'm in the minority here but let me explain. the film takes place in harrisburg, pa in 1988 during an unseasonably warm winter.

seen at: amc old pasadena 8, pasadena, ca (in sdds) paul verhoeven's last movie, showgirls, had a bad script, bad acting, and a "plot" (i use the word in its loosest possible sense) that served only to allow lots of sex and nudity. it stank. starship troopers has a bad script, bad acting, and a "plot" that serves only to allow lots of violence and gore. it stinks. nobody will watch this movie for the plot, ...
there's some movies i enjoy even though i know i probably shouldn't and have a difficult time trying to explain why i did. "lucky numbers" is a perfect example of this because it's such a blatant rip-off of "fargo" and every movie based on an elmore leonard novel and yet it somehow still works for me. i know i'm in the minority here but let me explain. the film takes place in harrisburg, pa in 1988 during an unseasonably warm winter. ...

seen at: amc old pasadena 8, pasadena, ca (in sdds) paul verhoeven's last movie, showgirls, had a bad script, bad acting, and a "plot" (i use the word in its loosest possible sense) that served only to allow lots of sex and nudity. it stank. starship troopers has a bad script, bad acting, and a "plot" that serves only to allow lots of violence and gore. it stinks. nobody will watch this movie for the plot, ...
there's some movies i enjoy even though i know i probably shouldn't and have a difficult time trying to explain why i did. "lucky numbers" is a perfect example of this because it's such a blatant rip-off of "fargo" and every movie based on an elmore leonard novel and yet it somehow still works for me. i know i'm in the minority here but let me explain. the film takes place in harrisburg, pa in 1988 during an unseasonably warm winter.

seen at: amc old pasadena 8, pasadena, ca (in sdds) paul verhoeven's last movie, showgirls, had a bad script, bad acting, and a "plot" (i use the word in its loosest possible sense) that served only to allow lots of sex and nudity. it stank. starship troopers has a bad script, bad acting, and a "plot" that serves only to allow lots of violence and gore. it stinks. nobody will watch this movie for the plot.

the rich legacy of cinema has left us with certain indelible images. the tinkling christmas tree bell in "it's a wonderful life." bogie's speech at the airport in "casablanca." little elliott's flying bicycle, silhouetted by the moon in "e.t." and now, "starship troopers" director paul verhoeven adds one more image that will live in our memories forever: doogie houser doing a vulcan mind meld with a giant slug. "starship troopers," loosely based on
there's some movies i enjoy even though i know i probably shouldn't and have a difficult time trying to explain why i did. "lucky numbers" is a perfect example of this because it's such a blatant rip-off of "fargo" and every movie based on an elmore leonard novel and yet it somehow still works for me. i know i'm in the minority here but let me explain. the film takes place in harrisburg, pa in 1988 during an unseasonably warm winter. ...

seen at: amc old pasadena 8, pasadena, ca (in sdds) paul verhoeven's last movie, showgirls, had a bad script, bad acting, and a "plot" (i use the word in its loosest possible sense) that served only to allow lots of sex and nudity. it stank. starship troopers has a bad script, bad acting, and a "plot" that serves only to allow lots of violence and gore. it stinks. nobody will watch this movie for the plot, ...

the rich legacy of cinema has left us with certain indelible images. the tinkling christmas tree bell in "it's a wonderful life." bogie's speech at the airport in "casablanca." little elliott's flying bicycle, silhouetted by the moon in "e.t." and now, "starship troopers" director paul verhoeven adds one more image that will live in our memories forever: doogie houser doing a vulcan mind meld with a giant slug. "starship troopers," loosely based on
Setting up a Classifier
Setting up a Classifier

• What we want:

\[ p(\smiley | w_1, w_2, ..., w_n) > p(\frown | w_1, w_2, ..., w_n) \]
Setting up a Classifier

• What we want:

\[ p(\text{😊} \mid w_1, w_2, ..., w_n) > p(\text{😢} \mid w_1, w_2, ..., w_n) \]

• What we know how to build:
Setting up a Classifier

• What we want:

\[ p(☺ | w_1, w_2, ..., w_n) > p(☺ | w_1, w_2, ..., w_n) \]?

• What we know how to build:

• A language model for each class
Setting up a Classifier

- What we want:

  \[ p(☺ \mid w_1, w_2, ..., w_n) > p(☻ \mid w_1, w_2, ..., w_n) ? \]

- What we know how to build:
  - A language model for each class
    - \[ p(w_1, w_2, ..., w_n \mid ☺) \]
Setting up a Classifier

• What we want:

$$p(☺ | w_1, w_2, ..., w_n) > p(☹ | w_1, w_2, ..., w_n)$$

• What we know how to build:

• A language model for each class

• $p(w_1, w_2, ..., w_n | ☺)$

• $p(w_1, w_2, ..., w_n | ☹)$
Bayes’ Theorem

By the definition of conditional probability:

\[ P(A, B) = P(B)P(A \mid B) = P(A)P(B \mid A) \]

we can show:

\[ P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \]

Seemingly trivial result from 1763; interesting consequences...
A “Bayesian” Classifier

\[ p(R \mid w_1, w_2, \ldots, w_n) = \frac{p(R)p(w_1, w_2, \ldots, w_n \mid R)}{p(w_1, w_2, \ldots, w_n)} \]

\[ \max_{R \in \{\tilde{\cdot}, \check{\cdot}\}} p(R \mid w_1, w_2, \ldots, w_n) = \max_{R \in \{\tilde{\cdot}, \check{\cdot}\}} p(R)p(w_1, w_2, \ldots, w_n \mid R) \]
Naive Bayes Classifier

No dependencies among words!
NB on Movie Reviews

- Train models for positive, negative
- For each review, find higher posterior
- Which word probability ratios are highest?

```python
>>> classifier.show_most_informative_features(5)

classifier.show_most_informative_features(5)
Most Informative Features
contains(outstanding) = True              pos : neg    =     14.1 : 1.0
contains(mulan) = True              pos : neg    =      8.3 : 1.0
contains(seagal) = True              neg : pos    =      7.8 : 1.0
contains(wonderfully) = True              pos : neg    =      6.6 : 1.0
contains(damon) = True              pos : neg    =      6.1 : 1.0
```
What’s Wrong With NB?

- What happens for word dependencies are strong?
- What happens when some words occur only once?
- What happens when the classifier sees a new word?
ML for Naive Bayes

• Recall: \( p(+ \mid \text{Damon movie}) \)

\[
p(+ \mid \text{Damon}) = p(\text{Damon} \mid +) p(\text{movie} \mid +) p(+)
\]

• If corpus of positive reviews has 1000 words, and “Damon” occurs 50 times,

\[
p_{\text{ML}}(\text{Damon} \mid +) = ?
\]

• If pos. corpus has “Affleck” 0 times,

\[
p(+ \mid \text{Affleck Damon movie}) = ?
\]
Will the Sun Rise Tomorrow?
Will the Sun Rise Tomorrow?

Laplace’s Rule of Succession:
On day $n+1$, we’ve observed that the sun has risen $s$ times before.

$$P_{Lap}(S_{n+1} = 1 \mid S_1 + \cdots + S_n = s) = \frac{s + 1}{n + 2}$$

What’s the probability on day 0?
On day 1?
On day $10^6$?
Start with prior assumption of equal rise/not-rise probabilities; update after every observation.
SpamAssassin Features

- Basic (Naïve) Bayes spam probability
- Mentions: Generic Viagra
- Regex: millions of (dollar) ((dollar) NN,NNN,NNN.NN)
- Phrase: impress ... girl
- Phrase: ‘Prestigious Non-Accredited Universities’
- From: starts with many numbers
- Subject is all capitals
- HTML has a low ratio of text to image area
- Relay in RBL, http://www.mail-abuse.com/enduserinfo_rbl.html
- RCVD line looks faked
- http://spamassassin.apache.org/tests_3_3_x.html
Naive Bayes is Not So Naive

- Very fast learning and testing (basically just count words)
- Low storage requirements
- Very good in domains with many equally important features
- More robust to irrelevant features than many learning methods
  
  Irrelevant features cancel each other without affecting results
Naive Bayes is Not So Naive

- More robust to concept drift (changing class definition over time)
- Naive Bayes won 1\textsuperscript{st} and 2\textsuperscript{nd} place in KDD-CUP 97 competition out of 16 systems

Goal: Financial services industry direct mail response prediction: Predict if the recipient of mail will actually respond to the advertisement – 750,000 records.

- A good dependable baseline for text classification (but not the best)!
Classification Using Vector Spaces

- In vector space classification, training set corresponds to a labeled set of points (equivalently, vectors)

- **Premise 1:** Documents in the same class form a contiguous region of space

- **Premise 2:** Documents from different classes don’t overlap (much)

- Learning a classifier: build surfaces to delineate classes in the space
Documents in a Vector Space
Test Document of what class?
Test Document = Government

Our focus: how to find good separators

Is this similarity hypothesis true in general?
Definition of centroid

\[ \tilde{\mu}(c) = \frac{1}{|D_c|} \]

- Where \( D_c \) is the set of all documents that belong to class \( c \) and \( v(d) \) is the vector space representation of \( d \).

- Note that centroid will in general not be a unit vector even when the inputs are unit vectors.
Rocchio classification

- Rocchio forms a simple representative for each class: the centroid/prototype
- Classification: nearest prototype/centroid
- It does not guarantee that classifications are consistent with the given training data
- Remember: Used with two classes for relevance feedback
Rocchio classification

- Little used outside text classification
  - It has been used quite effectively for text classification
  - But in general worse than Naïve Bayes
- Again, cheap to train and test documents
**k Nearest Neighbor Classification**

- kNN = $k$ Nearest Neighbor

- To classify a document $d$:
  - Define $k$-neighborhood as the $k$ nearest neighbors of $d$
  - Pick the majority class label in the $k$-neighborhood

Sec. 14.3
Example: $k=6$ (6NN)
Nearest-Neighbor Learning
Nearest-Neighbor Learning

- Learning: just store the labeled training examples $D$
- Testing instance $x$ (under 1NN):
  - Compute similarity between $x$ and all examples in $D$.
  - Assign $x$ the category of the most similar example in $D$.
- Does not compute anything beyond storing the examples
Nearest-Neighbor Learning

- Learning: just store the labeled training examples $D$
- Testing instance $x$ (under 1NN):
  - Compute similarity between $x$ and all examples in $D$.
  - Assign $x$ the category of the most similar example in $D$.
- Does not compute anything beyond storing the examples
- Also called:
  - Case-based learning
  - Memory-based learning
  - Lazy learning
Nearest-Neighbor Learning

- Learning: just store the labeled training examples $D$
- Testing instance $x$ (under 1NN):
  - Compute similarity between $x$ and all examples in $D$.
  - Assign $x$ the category of the most similar example in $D$.
- Does not compute anything beyond storing the examples
- Also called:
  - Case-based learning
  - Memory-based learning
  - Lazy learning
- Rationale of kNN: contiguity hypothesis
k Nearest Neighbor

- Using only the closest example (1NN) subject to errors due to:
  - A single atypical example.
  - Noise (i.e., an error) in the category label of a single training example.

- More robust: find the $k$ examples and return the majority category of these $k$

- $k$ is typically odd to avoid ties; 3 and 5 are most common
kNN decision boundaries

kNN gives locally defined decision boundaries between classes – far away points do not influence each classification decision (unlike in Naïve Bayes, Rocchio, etc.)

Boundaries are in principle arbitrary surfaces – but usually polyhedra.

- Government
- Science
- Arts
Illustration of 3 Nearest Neighbor for Text Vector Space
3 Nearest Neighbor vs. Rocchio

- Nearest Neighbor tends to handle polymorphic categories better than Rocchio/NB.
kNN: Discussion

- No feature selection necessary
- No training necessary
- Scales well with large number of classes
  - Don’t need to train \( n \) classifiers for \( n \) classes
- Classes can influence each other
  - Small changes to one class can have ripple effect
- May be expensive at test time
- In most cases it’s more accurate than NB or Rocchio
Let’s test our intuition

- Can a bag of words always be viewed as a vector space?
- What about a bag of features?
- Can we always view a standing query as a region in a vector space?
- What about Boolean queries on terms?
- What do “rectangles” equate to?
Bias vs. capacity – notions and terminology

- Consider asking a botanist: Is an object a tree?
  - Too much capacity, low bias
    - Botanist who memorizes
    - Will always say “no” to new object (e.g., different # of leaves)
  - Not enough capacity, high bias
    - Lazy botanist
    - Says “yes” if the object is green
- You want the middle ground

(Example due to C. Burges)
kNN vs. Naive Bayes

- Bias/Variance tradeoff
  - Variance ≈ Capacity
- kNN has high variance and low bias.
  - Infinite memory
- NB has low variance and high bias.
  - Linear decision surface (hyperplane – see later)
Bias vs. variance:
Choosing the correct model capacity
Representations of text are usually very high dimensional

High-bias algorithms that prevent overfitting should generally work best in high-dimensional space

For most text categorization tasks, there are many relevant features and many irrelevant ones
Which classifier do I use for a given text classification problem?

- Is there a learning method that is optimal for all text classification problems?
- No, because there is a tradeoff between bias and variance.

Factors to take into account:
- How much training data is available?
- How simple/complex is the problem? (linear vs. nonlinear decision boundary)
- How noisy is the data?
- How stable is the problem over time?
  - For an unstable problem, its better to use a simple and robust classifier.
Clustering
Clustering

• Unsupervised structure discovery
• Exploratory data analysis
• Clustering for word senses
• Clustering for retrieval effectiveness
  • Some have also proposed clustering for efficiency
thing. She was talking at a party thrown at Daphne's restaurant in have turned it into the hot dinner-party topic. The comedy is the selection for the World Cup party, which will be announced on May 1 in the 1983 general election for a party which, when it could not bear to attack the Scottish National Party, who look set to seize Perth and that had been passed to a second party who made a financial decision the by-pass there will be a street party. "Then," he says, "we are going number-crunchers within the Labour party, there now seems little doubt political tradition and the same party. They are both relatively Anglophilic he told Tony Blair's modernised party they must not retreat into "warm "Oh no, I'm just here for the party," they said. "I think it's terrible A future obliges each party to the contract to fulfil it by be signed by or on behalf of each party to the contract." Mr David N
What Good are Word Senses?

- thing. She was talking at a party thrown at Daphne's restaurant in
- have turned it into the hot dinner-party topic. The comedy is the
- selection for the World Cup party, which will be announced on May 1
- in the 1983 general election for a party which, when it could not bear to
- to attack the Scottish National Party, who look set to seize Perth and
- that had been passed to a second party who made a financial decision
- the by-pass there will be a street party. "Then," he says, "we are going
- number-crunchers within the Labour party, there now seems little doubt
- political tradition and the same party. They are both relatively Anglophilic
- he told Tony Blair's modernised party they must not retreat into "warm
- "Oh no, I'm just here for the party," they said. "I think it's terrible
- A future obliges each party to the contract to fulfil it by
- be signed by or on behalf of each party to the contract." Mr David N
What Good are Word Senses?

- thing. She was talking at a party thrown at Daphne's restaurant in have turned it into the hot dinner-party topic. The comedy is the selection for the World Cup party, which will be announced on May 1 the by-pass there will be a street party. "Then," he says, "we are going "Oh no, I'm just here for the party," they said. "I think it's terrible

- in the 1983 general election for a party which, when it could not bear to to attack the Scottish National Party, who look set to seize Perth and number-crunchers within the Labour party, there now seems little doubt political tradition and the same party. They are both relatively Anglophilic he told Tony Blair's modernised party they must not retreat into "warm

- that had been passed to a second party who made a financial decision A future obliges each party to the contract to fulfil it by be signed by or on behalf of each party to the contract." Mr David N
What Good are Word Senses?

- John threw a “rain forest” party last December. His living room was full of plants and his box was playing Brazilian music ...
What Good are Word Senses?

- Replace word $w$ with sense $s$
  - **Splits** $w$ into senses: distinguishes this token of $w$ from tokens with sense $t$
  - **Groups** $w$ with other words: groups this token of $w$ with tokens of $x$ that also have sense $s$
What Good are Word Senses?

- number-crunchers within the Labour party, there now seems little doubt political tradition and the same party. They are both relatively Anglophilic he told Tony Blair's modernised party they must not retreat into "warm thing. She was talking at a party thrown at Daphne's restaurant in have turned it into the hot dinner-party topic. The comedy is the selection for the World Cup party, which will be announced on May 1 the by-pass there will be a street party. "Then," he says, "we are going "Oh no, I'm just here for the party," they said. "I think it's terrible

- an appearance at the annual awards bash, but feels in no fit state to -known families at a fundraising bash on Thursday night for Learning Who was paying for the bash? The only clue was the name Asprey, Mail, always hosted the annual bash for the Scottish Labour front-popular. Their method is to bash sense into criminals with a short, just cut off people's heads and bash their brains out over the floor,
What Good are Word Senses?

- number-crunchers within the Labour party, there now seems little doubt political tradition and the same party. They are both relatively Anglophilic. he told Tony Blair's modernised party they must not retreat into "warm thing. She was talking at a party thrown at Daphne's restaurant in have turned it into the hot dinner-party topic. The comedy is the selection for the World Cup party, which will be announced on May 1 the by-pass there will be a street party. "Then," he says, "we are going "Oh no, I'm just here for the party," they said. "I think it's terrible an appearance at the annual awards bash, but feels in no fit state to -known families at a fundraising bash on Thursday night for Learning Who was paying for the bash? The only clue was the name Asprey, Mail, always hosted the annual bash for the Scottish Labour front-

- popular. Their method is to bash sense into criminals with a short, just cut off people's heads and bash their brains out over the floor,
What Good are Word Senses?
What Good are Word Senses?

- Semantics / Text understanding
  - Axioms about TRANSFER apply to (some tokens of) throw
  - Axioms about BUILDING apply to (some tokens of) bank
What Good are Word Senses?

- Semantics / Text understanding
  - Axioms about TRANSFER apply to (some tokens of) *throw*
  - Axioms about BUILDING apply to (some tokens of) *bank*
- Machine translation
What Good are Word Senses?

- Semantics / Text understanding
  - Axioms about TRANSFER apply to (some tokens of) throw
  - Axioms about BUILDING apply to (some tokens of) bank
- Machine translation
- Info retrieval / Question answering / Text categ.
  - Query or pattern might not match document exactly
What Good are Word Senses?

- Semantics / Text understanding
  - Axioms about TRANSFER apply to (some tokens of) throw
  - Axioms about BUILDING apply to (some tokens of) bank
- Machine translation
- Info retrieval / Question answering / Text categ.
  - Query or pattern might not match document exactly
- Backoff for just about anything
  - what word comes next? (speech recognition, language ID, ...)
    - trigrams are sparse but tri-meanings might not be
  - bilexical PCFGs: \( p(S[\text{devour}] \rightarrow \text{NP}[\text{lion}] \text{VP}[\text{devour}] | S[\text{devour}]) \)
    - approximate by \( p(S[\text{EAT}] \rightarrow \text{NP}[\text{lion}] \text{VP}[\text{EAT}] | S[\text{EAT}]) \)
What Good are Word Senses?

- Semantics / Text understanding
  - Axioms about TRANSFER apply to (some tokens of) **throw**
  - Axioms about BUILDING apply to (some tokens of) **bank**

- Machine translation
- Info retrieval / Question answering / Text categ.
  - Query or pattern might not match document exactly

- Backoff for just about anything
  - what word comes next? (speech recognition, language ID, ...)
    - trigrams are sparse but tri-meanings might not be
  - bilexical PCFGs: \( p(S[\text{devour}] \rightarrow NP[\text{lion}] \; VP[\text{devour}] \mid S[\text{devour}]) \)
    - approximate by \( p(S[\text{EAT}] \rightarrow NP[\text{lion}] \; VP[\text{EAT}] \mid S[\text{EAT}]) \)

- Speaker’s real intention is senses; words are a noisy channel
Cues to Word Sense
Cues to Word Sense

- Adjacent words (or their senses)
Cues to Word Sense

- Adjacent words (or their senses)
- Grammatically related words (subject, object, ...)

Cues to Word Sense

- Adjacent words (or their senses)
- Grammatically related words (subject, object, ...)
- Other nearby words
Cues to Word Sense

- Adjacent words (or their senses)
- Grammatically related words (subject, object, ...)
- Other nearby words
- Topic of document
Cues to Word Sense

- Adjacent words (or their senses)
- Grammatically related words (subject, object, ...)
- Other nearby words
- Topic of document
- Sense of other tokens of the word in the same document
Words as Vectors

- Represent each word type $w$ by a point in $k$-dimensional space
  - e.g., $k$ is size of vocabulary
  - the 17th coordinate of $w$ represents strength of $w$'s association with vocabulary word 17
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents strength of \( w \)’s association with vocabulary word 17
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents \textit{strength} of \( w \)’s association with vocabulary word 17

\[(0, 0, 3, 1, 0, 7, \ldots, 1, 0)\]
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents strength of \( w \)’s association with vocabulary word 17

- \( \text{aardvark} \): \( (0, 0, 3, 1, 0, 7, \ldots) \)
- \( \text{abacus} \): \( (0, 0, 3, 1, 0, 7, \ldots) \)
- \( \text{abandoned} \): \( (0, 0, 3, 1, 0, 7, \ldots) \)
- \( \text{abbot} \): \( (0, 0, 3, 1, 0, 7, \ldots) \)
- \( \text{abduct} \): \( (0, 0, 3, 1, 0, 7, \ldots) \)
- \( \text{above} \): \( (0, 0, 3, 1, 0, 7, \ldots) \)
- \( \text{zygote} \): \( (1, 0) \)
- \( \text{zymurgy} \): \( (1, 0) \)
Words as Vectors

- Represent each word type $w$ by a point in $k$-dimensional space
  - e.g., $k$ is size of vocabulary
  - the 17$^{th}$ coordinate of $w$ represents strength of $w$’s association with vocabulary word 17

From corpus:

Arlen Specter abandoned the Republican party.
There were lots of abbots and nuns dancing at that party.
The party above the art gallery was, above all, a laboratory for synthesizing zygotes and beer.
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents strength of \( w \)'s association with vocabulary word 17

From corpus:
- Arlen Specter abandoned the Republican party.
- There were lots of abbots and nuns dancing at that party.
- The party above the art gallery was, above all, a laboratory for synthesizing zygotes and beer.
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents strength of \( w \)'s association with vocabulary word 17

From corpus: Arlen Specter abandoned the Republican party.
There were lots of abbots and nuns dancing at that party.
The party above the art gallery was, above all, a laboratory for synthesizing zygotes and beer.
Words as Vectors

- Represent each word type $w$ by a point in $k$-dimensional space
  - e.g., $k$ is size of vocabulary
  - the 17th coordinate of $w$ represents strength of $w$'s association with vocabulary word 17

(aardvark, abacus, abandoned, abbot, abduct, above, abondon) = (0, 0, 3, 1, 0, 7, 0) ...

zygote, zymurgy = (1, 0)
Words as Vectors

- Represent each word type $w$ by a point in $k$-dimensional space
  - e.g., $k$ is size of vocabulary
  - the 17$^{th}$ coordinate of $w$ represents strength of $w$’s association with vocabulary word 17

(0, 0, 3, 1, 0, 7, ...)

aardvark, abacus, abandoned, abbot, abduct, above

zygote, zymurgy

how might you measure this?
Words as Vectors

- Represent each word type $w$ by a point in $k$-dimensional space
  - e.g., $k$ is size of vocabulary
  - the 17th coordinate of $w$ represents strength of $w$’s association with vocabulary word 17
  - how often words appear next to each other

(aardvark, abacus, abandoned, abbot, abduct, above, abandonded, ...)
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents strength of \( w \)'s association with vocabulary word 17

- How often words appear next to each other
- How often words appear near each other

(aardvark, abacus, abandoned, abbot, abduct, above, zygote, zymurgy)
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents strength of \( w \)'s association with vocabulary word 17

- how often words appear next to each other
- how often words appear near each other
- how often words are syntactically linked

\[(0, 0, 3, 1, 0, 7, \ldots, 1, 0)\]
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{\text{th}}\) coordinate of \( w \) represents strength of \( w \)’s association with vocabulary word 17

- how often words appear next to each other
- how often words appear near each other
- how often words are syntactically linked
- should correct for commonness of word (e.g., “above”)
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\(^{th} \) coordinate of \( w \) represents \textbf{strength} of \( w \)’s association with vocabulary word 17

\begin{itemize}
  \item aardvark
  \item abacus
  \item abandoned
  \item abbot
  \item abduct
  \item above
  \item zygote
  \item zymurgy
\end{itemize}

\begin{itemize}
  \item (0, 0, 3, 1, 0, 7, \ldots)
  \item (1, 0)
\end{itemize}
Words as Vectors

- Represent each word type $w$ by a point in $k$-dimensional space
  - e.g., $k$ is size of vocabulary
  - the 17th coordinate of $w$ represents strength of $w$’s association with vocabulary word 17

- Plot all word types in $k$-dimensional space

(aardvark, 0, 0, 3, 1, 0, 7, ...)

(abacus, abandoned, abbot, abduct, above, ...)

(zygote, 1, 0)

(zymurgy, ...)
Words as Vectors

- Represent each word type \( w \) by a point in \( k \)-dimensional space
  - e.g., \( k \) is size of vocabulary
  - the 17\textsuperscript{th} coordinate of \( w \) represents \textbf{strength} of \( w \)’s association with vocabulary word 17

\begin{align*}
aardvark & \quad (0, \ 0, \ 3, \ 1, \ 0, \ 7, \ \ldots) \\
abacus & \\
abandoned & \\
abbot & \\
abduct & \\
above & \\
\vdots & \\
zygote & (1, \ 0) \\
zymurgy &
\end{align*}

- Plot all word types in \( k \)-dimensional space
- Look for \textbf{clusters} of close-together types
Learning Classes by Clustering

- Plot all word types in k-dimensional space
- Look for clusters of close-together types

Plot in k dimensions (here k=3)
Learning Classes by Clustering

- Plot all word types in k-dimensional space
- Look for clusters of close-together types

Plot in k dimensions (here k=3)
Learning Classes by Clustering

- Plot all word types in k-dimensional space
- Look for **clusters** of close-together types

Plot in k dimensions (here k=3)
Bottom-Up Clustering

- Start with one cluster per point
- Repeatedly merge 2 closest clusters
  - Single-link: \( \text{dist}(A,B) = \min \text{ dist}(a,b) \) for \( a \in A \), \( b \in B \)
  - Complete-link: \( \text{dist}(A,B) = \max \text{ dist}(a,b) \) for \( a \in A \), \( b \in B \)
- Produces a dendrogram
Bottom-Up Clustering – Single-Link

Each word type is a single-point cluster.
Bottom-Up Clustering – Single-Link

Each word type is a single-point cluster.

Example from Manning & Schütze
Bottom-Up Clustering – Single-Link

Each word type is a single-point cluster.
Bottom-Up Clustering – Single-Link

Each word type is a single-point cluster.

Example from Manning & Schütze
Bottom-Up Clustering – Single-Link

Each word type is a single-point cluster.

Example from Manning & Schütze
Bottom-Up Clustering – Single-Link

Again, merge closest pair of clusters:

**Single-link:** clusters are close if *any* of their points are

\[
dist(A,B) = \min \{dist(a,b) \mid a \in A, b \in B\}
\]
Bottom-Up Clustering – Single-Link

Again, merge closest pair of clusters:

Single-link: clusters are close if any of their points are

\[ \text{dist}(A, B) = \min \text{ dist}(a, b) \text{ for } a \in A, \ b \in B \]

Each word type is a single-point cluster.

Example from Manning & Schütze
Bottom-Up Clustering – Single-Link

Again, merge closest pair of clusters:

**Single-link:** clusters are close if *any* of their points are

$$\text{dist}(A, B) = \min \text{ dist}(a, b) \text{ for } a \in A, b \in B$$

each word type is a single-point cluster

Again, merge closest pair of clusters:
Again, merge closest pair of clusters:

**Single-link**: clusters are close if any of their points are

$$\text{dist}(A,B) = \min \text{ dist}(a,b) \text{ for } a \in A, \ b \in B$$

Fast, but tend to get long, stringy, meandering clusters
Bottom-Up Clustering – Single-Link

Again, merge closest pair of clusters:

**Single-link**: clusters are close if any of their points are

\[ \text{dist}(A,B) = \min \text{dist}(a,b) \text{ for } a \in A, b \in B \]

Fast, but tend to get long, stringy, meandering clusters
Again, merge closest pair of clusters:

**Single-link:** clusters are close if any of their points are

$$\text{dist}(A,B) = \min \text{ dist}(a,b) \quad \text{for } a \in A, \ b \in B$$

Fast, but tend to get long, stringy, meandering clusters
Again, merge closest pair of clusters:

**Single-link**: clusters are close if any of their points are

\[
\text{dist}(A,B) = \min \text{ dist}(a,b) \text{ for } a \in A, b \in B
\]

Fast, but tend to get long, stringy, meandering clusters
Bottom-Up Clustering – Complete-Link

example from Manning & Schütze
Bottom-Up Clustering – Complete-Link

Again, merge closest pair of clusters:

**Complete-link:** clusters are close only if all of their points are

\[
\text{dist}(A, B) = \max \text{ dist}(a, b) \text{ for } a \in A, b \in B
\]
Bottom-Up Clustering – Complete-Link

Again, merge closest pair of clusters:

**Complete-link**: clusters are close only if all of their points are

\[ \text{dist}(A,B) = \max \text{ dist}(a,b) \text{ for } a \in A, \ b \in B \]
Bottom-Up Clustering – Complete-Link

Again, merge closest pair of clusters:

**Complete-link:** clusters are close only if all of their points are

\[
\text{dist}(A, B) = \max \text{ dist}(a, b) \quad \text{for } a \in A, \ b \in B
\]
Bottom-Up Clustering – Complete-Link

Again, merge closest pair of clusters:

**Complete-link**: clusters are close only if all of their points are

\[ \text{dist}(A,B) = \max \text{dist}(a,b) \text{ for } a \in A, b \in B \]
Again, merge closest pair of clusters:

**Complete-link:** clusters are close only if all of their points are

\[ \text{dist}(A,B) = \max \text{dist}(a,b) \text{ for } a \in A, b \in B \]
Bottom-Up Clustering – Complete-Link

Again, merge closest pair of clusters:

**Complete-link:** clusters are close only if all of their points are

\[
\text{dist}(A,B) = \max \text{ dist}(a,b) \text{ for } a \in A, \ b \in B
\]

Slow to find closest pair – need quadratically many distances
Again, merge closest pair of clusters:

**Complete-link:** clusters are close only if all of their points are

\[ \text{dist}(A,B) = \max \text{dist}(a,b) \text{ for } a \in A, b \in B \]

Slow to find closest pair – need quadratically many distances
Bottom-Up Clustering Heuristics
Bottom-Up Clustering

- Start with one cluster per point
- Repeatedly merge 2 closest clusters
  - **Single-link:** \( \text{dist}(A,B) = \min \text{dist}(a,b) \) for \( a \in A, b \in B \)
  - **Complete-link:** \( \text{dist}(A,B) = \max \text{dist}(a,b) \) for \( a \in A, b \in B \)
    - too slow to update cluster distances after each merge; but \( \exists \) alternatives!
Bottom-Up Clustering

- Start with one cluster per point
- Repeatedly merge 2 closest clusters
  - Single-link: $\text{dist}(A,B) = \min \text{ dist}(a,b)$ for $a \in A$, $b \in B$
  - Complete-link: $\text{dist}(A,B) = \max \text{ dist}(a,b)$ for $a \in A$, $b \in B$
    - too slow to update cluster distances after each merge; but $\exists$ alternatives!
  - Average-link: $\text{dist}(A,B) = \text{mean dist}(a,b)$ for $a \in A$, $b \in B$
  - Centroid-link: $\text{dist}(A,B) = \text{dist}(\text{mean}(A),\text{mean}(B))$
Bottom-Up Clustering

- Start with one cluster per point
- Repeatedly merge 2 closest clusters
  - Single-link: $\text{dist}(A,B) = \min \text{dist}(a,b)$ for $a \in A$, $b \in B$
  - Complete-link: $\text{dist}(A,B) = \max \text{dist}(a,b)$ for $a \in A$, $b \in B$
    - too slow to update cluster distances after each merge; but $\exists$ alternatives!
  - Average-link: $\text{dist}(A,B) = \text{mean dist}(a,b)$ for $a \in A$, $b \in B$
  - Centroid-link: $\text{dist}(A,B) = \text{dist(\text{mean}(A),\text{mean}(B))}$
- Stop when clusters are “big enough”
  - e.g., provide adequate support for backoff (on a development corpus)
Bottom-Up Clustering

- Start with one cluster per point
- Repeatedly merge 2 closest clusters
  - Single-link: $\text{dist}(A,B) = \min \text{dist}(a,b)$ for $a \in A, b \in B$
  - Complete-link: $\text{dist}(A,B) = \max \text{dist}(a,b)$ for $a \in A, b \in B$
    - too slow to update cluster distances after each merge; but $\exists$ alternatives!
  - Average-link: $\text{dist}(A,B) = \text{mean} \text{dist}(a,b)$ for $a \in A, b \in B$
  - Centroid-link: $\text{dist}(A,B) = \text{dist}(\text{mean}(A),\text{mean}(B))$
- Stop when clusters are “big enough”
  - e.g., provide adequate support for backoff (on a development corpus)
- Some flexibility in defining $\text{dist}(a,b)$
  - Might not be Euclidean distance; e.g., use vector angle
EM Clustering (for k clusters)
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”

- **Expectation step:** Use current parameters (and observations) to reconstruct hidden structure
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”

- **Expectation step:** Use current parameters (and observations) to reconstruct hidden structure
- **Maximization step:** Use that hidden structure (and observations) to reestimate parameters
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”

- **Expectation step:** Use current parameters (and observations) to reconstruct hidden structure
- **Maximization step:** Use that hidden structure (and observations) to reestimate parameters
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”

- **Expectation step:** Use current parameters (and observations) to reconstruct hidden structure
- **Maximization step:** Use that hidden structure (and observations) to reestimate parameters

- **Parameters:** k points representing cluster centers
EM Clustering (for k clusters)

- EM algorithm
  - Viterbi version – called “k-means clustering”
  - Full EM version – called “Gaussian mixtures”

- **Expectation step**: Use current parameters (and observations) to reconstruct hidden structure
- **Maximization step**: Use that hidden structure (and observations) to reestimate parameters

- **Parameters**: k points representing cluster centers
- **Hidden structure**: for each data point (word type), which center generated it?
Cluster Hypothesis

• Keith van Rijsbergen: “Closely associated documents tend to be relevant to the same requests.”
Cluster Hypothesis

Precision in of the 5 nearest neighbors of relevant documents
But Does It Help Retrieval?

- Cluster retrieval

- Smoothing with hard clusters

- Smoothing with soft clusters

- Last two more effective (cf. topic models)

\[
P(Q|C_j) = \prod_{i=1}^{n} P(q_i|C_j)
\]

\[
P(w|D) = (1 - \lambda - \delta) \frac{f_{w,D}}{|D|} + \delta \frac{f_{w,C_j}}{|C_j|} + \lambda \frac{f_{w,Coll}}{|Coll|}
\]

\[
P(w|D) = (1 - \lambda - \delta) \frac{f_{w,D}}{|D|} + \delta \sum_{C_j} \frac{f_{w,C_j}}{|C_j|} P(D|C_j) + \lambda \frac{f_{w,Coll}}{|Coll|}
\]