150B/355B
Introduction to Machine Learning for Social Science
TA Section 6

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February 16, 2018

Road Map

1. K Nearest Neighbor

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2. Text Preprocessing

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3. Dictionary method

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2. Text Preprocessing
3. Dictionary method
4. R Exercise

K Nearest Neighbors

We assume some relationship between label Y and predictors $X = (X_1, X_2, ..., X_p)$, such that:

$$Y = f(X) + \epsilon$$

where f is fixed but unknown function of $X_1, ..., X_p$, and ϵ is a random error term that is is independent of X and has mean zero. .

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Machine learning: estimating f with $\hat{f}$.

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- Linear probability regression
- Logit regression
- LASSO

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$\rightsquigarrow$ parametric models

- Advantage: simplifies estimation of f, interpretability of the relationship between X and Y
- Disadvantage: what if our assumption of f is wrong?

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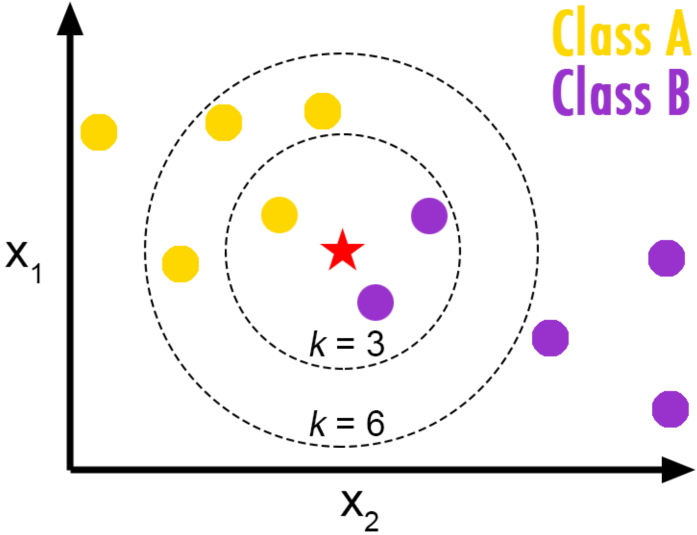
- Disadvantage: what if our assumption of f is wrong? $\rightsquigarrow$ nonparametric models

K Nearest Neighbors

KNN: a nonparametric model



K Nearest Neighbors

Nonparametric model

- No explicit assumption about the functional form of f

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- No fixed parameters (no β coefficients)

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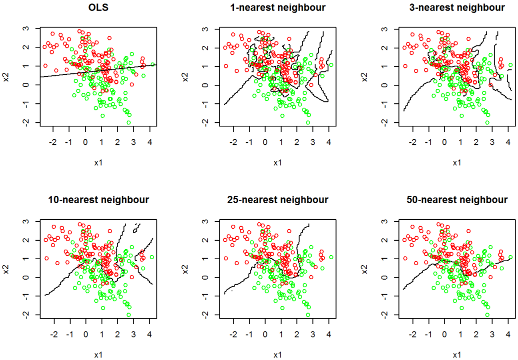
Nonparametric model

- No explicit assumption about the functional form of f
- No fixed parameters (no β coefficients)
- No or little training: all computation delayed until prediction

K Nearest Neighbors



Choice of K has a drastic effect on the KNN classifier:

As K increases, the decision boundary is less and less flexible (higher bias, lower variance)

Text Preprocessing

Task: Convert raw documents into a document-term matrix

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Text Preprocessing

Task: Convert raw documents into a document-term matrix

- Step 1: Convert raw documents (html, pdf) into a corpus (a csv file in which each document is a row, one column is text, other columns are metadata like author, date)
- Step 2: Pre-processing
    1) Remove capitalization, punctuation
    2) Discard Word Order: (Bag of Words Assumption)
    3) Discard stop words
    4) Combine similar terms: Stem, Lemmatize
    5) Discard less useful features $\rightsquigarrow$ depends on application
    6) Other reduction, weighting
    7) Output: a Count vector for each document, each element counts occurrence of terms

Text Preprocessing

```
Four score and seven years ago our fathers brought forth on
this continent a new nation, conceived in liberty, and
dedicated to the proposition that all men are created
equal.
```

Text Preprocessing

`Four score and seven years ago our fathers brought forth on this continent a new nation, conceived in liberty, and dedicated to the proposition that all men are created equal.`

Step 1: Remove capitalization and punctuation:

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  - Unigram, Bigram, Trigram

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    - Unigram, Bigram, Trigram
    - Validation by human coders

Text Preprocessing

Step 1: Remove capitalization and punctuation:
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`four, score, and, seven, years, ago, our, fathers, brought, forth, on, this, continent, a, new, nation, conceived, in, liberty, and, dedicated, to, the, proposition, that, all, men, are, created, equal`

$\vdots$

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Step 3: Remove stop words:

- Stop words: `the, it, if, a, able, at, be, because...`

Text Preprocessing

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`four, score, seven, years, ago, fathers, brought, forth, continent, new, nation, conceived, liberty, dedicated, proposition, men, created, equal`

Step 4: Applying Stemming/Lemmatizing

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- Combine words with the same root

  `family, families, familial` $\rightarrow$ `famili`

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- Different ways to chop off end of word: Porter/Snowball/Lancaster stemmer

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Step 5: Create Count Vector

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Doc no.	ago	brought	seven	creat	conceiv	men	father
Doc 1	1	1	1	1	1	1	1
⋮	⋮						

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Step 6: Repeat steps 1-5 for each document

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`R Code, Section 1!`

Dictionary Method

Task: classify (measure) sentiment in texts (positive vs. negative; anger, fear, joy,...)

Method: Dictionary methods

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Method: Dictionary methods

Logic: Counting words – the higher proportion of words fall into an emotion category, the more likely that the document expresses that emotion.

Dictionaries

```
## 1      2-faced  negative
## 2      2-faces  negative
## 3           a+  positive
## 4     abnormal  negative
## 5      abolish  negative
## 6   abominable  negative
## 7   abominably  negative
## 8    abominate  negative
## 9  abomination  negative
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- Word weights / scores
  - Binary: $\{\text{Positive } (+1), \text{Negative } (\text{-}1)\}$

Dictionaries

```
## 1     abandon    -2
## 2   abandoned    -2
## 3    abandons    -2
## 4    abducted    -2
## 5   abduction    -2
## 6 abductions    -2
## 7       abhor    -3
## 8    abhorred    -3
## 9   abhorrent    -3
## 10     abhors    -3
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  - Binary: $\{$Positive $(+1)$, Negative (-1)$\}$
  - Numerical: $\{-2, -1, 1, 2\}$
- Non-sentiment dictionaries: Words about sports, food, places...

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$Y_i > \alpha \Rightarrow$ Positive Category

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$Y_i \approx \alpha$ Ambiguous

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- `R Code, Section 2!`