NLP Practical: Part I

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The Task: Beefing up Sentiment Classification

- Revive your code for Naive Bayes
- Revive your code for Sign Test
- Revive your code for Cross-validation
- New today: install a Support Vector Machine classifier
- New today: use a stemmer
- New today: bigrams as well as unigrams
- Submit code running on your lab accounts/machines.

Procedure/Timeline

- Practical Session Today:
  - How to develop the baseline system(s)
  - How to write the (baseline) Report 1 (20%; ticked)
- Practical Session Nov 7:
  - Move to doc2vec system
  - Some diagnostics
  - Write Report 2 (40%; assessed)
- Nov 9: Early (voluntary) Submission of Report 1 (guaranteed feedback)
- Nov 14: Submit Report 1 (baselines)
- Practical Session Nov 21: Text understanding
- Nov 21: Early submissions get feedback on their Report 1
- Nov 30: Submit Reports 2 and 3

Naive Bayes

- Naive Bayes Classifier:

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c|\vec{f}) = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{i=1}^{n} P(f_i|c)$$

Feature vector $\vec{f}$; most probable class $\hat{c}$; C set of classes.

- Write code that calculates $P(f_i|c)$ for each f_i of $\vec{f}$, using only the Training Set
- Then apply the classifier to the Test Set.
- When you design your data structures, please think about later parts of this practical where you will dynamically split data into Training and Test on the fly, and train on different sets each time (Cross-Validation)

Smoothing

- When using a NB classifier, you need to consider what to do with unseen words – words which occur in the development/test data but which do not occur in the training data at all
- Modify your calculation of log probabilities to use Laplace smoothing (add a small positive constant κ)
- Smoothing in general: Instead of

$$\frac{count(w_i, c)}{\sum_{w \in V} count(w, c)}$$

Use

$$\frac{count(w_i, c) + \kappa}{\sum_{w \in V} count(w, c) + \sum_{w \in V} \kappa}$$

- You will see a big improvement in NB Classification with Smoothing

N-Fold Cross-Validation

- For each split X – use all others for training, test on split X only
- The final performance is the average of the performances for each fold/split
- Apply sign test across splitting methods – why does it make sense to do so? What does it tell us if we pass this test? (optional)
- BTW, the way we have chosen to distribute data among splits is called stratified cross-validation (each split mirrors the distribution of classes observed in the overall data)

N-Fold Cross-Validation: Splitting

- Split data into N splits / folds / chuncks
- Different strategies for splitting:
  - Consecutive splitting:

    cv000–cv099 = Split 1
    cv100–cv199 = Split 2
    ...
  - Round-robin splitting (mod 10):

    cv000, cv010, cv020,... = Split 1
    cv001, cv011, cv021,... = Split 2
    ...
  - Random sampling/splitting: Not used here (but you may choose to split this way in a non-educational situation)

Relationship to Pang et al. (2002)

- Your rough target for the baseline is a simplified implementation of Pang et al (2002)
- And Pang is doing some additional things not included in your baseline:
  - POS-tagging
  - Maximum Entropy Classifier
- Replication sometimes requires interpretation on your part.

Statistical Tests – Comparing systems

- You will compare systems to each other, first NB vs NB smoothed.
- But: How do you know which system is “better”?
- Better in science means statistically better

Statistical Significance Testing

- Null Hypothesis: two result sets come from the same distribution
    - System 1 is (really) equally good as System 2
- First, choose a significance level (α), e.g., $\alpha = 0.01$
- We then try to reject the null hypothesis with at least probability $1 - \alpha$ (99% in this case)
- Rejecting the null hypothesis means showing that the observed result is very unlikely to have occurred by chance
- If we manage to do so, we can report a statistically significant difference at $\alpha = 0.01$
- Now – a particularly nice and simple test (non-parametric and paired): the sign test

Sign Test (non-parametric and paired)

- The sign test uses a binary event model
- Here, events correspond to documents ($2,000$ events in our case)
- Events have binary outcomes:
  - Positive: System 1 beats System 2 on this document
  - Negative: System 2 beats System 1 on this document
  - (Tie: System 1 and System 2 could also have the identical result on this document – more on this later)
- Call the probability of a positive outcome q (here $q = 0.5$)
- Binary distribution allows us to calculate the probability that, say, at least $1,247$ out of $2,000$ such binary events are positive
- Or otherwise the probability that at most 753 out of $2,000$ are negative

Binomial Distribution $B(N, q)$

- Probability of $X = k$ negative events out of N:

$$P_q(X = k|N) = \binom{N}{k} q^k (1 - q)^{N-k}$$

- At most k negative events:

$$P_q(X \leq k|N) = \sum_{i=0}^{k} \binom{N}{i} q^i (1 - q)^{N-i}$$

Binary Event Model and Statistical Tests

- If the probability of observing our events under Null Hypothesis is very small (smaller than our pre-selected significance level α, e.g., 1%), we can safely reject the Null hypothesis
- The calculated $P(X \leq k)$ directly gives us the probability p we are after
- This means there is only a 1% chance that System 1 does not beat System 2

Two-Tailed vs. One-Tailed Tests

- So far we've been testing difference in a specific direction:
  - The probability that, say, at least $1,247$ out of $2,000$ such binary events are positive [One-tailed test]
- A more conservative, rigorous test would be a non-directional one (though some debate on this)
  - Testing for statistically significant difference regardless of direction [Two-tailed test]
  - This is given by $2P(X \leq k)$ (because B(N, 0.5) is symmetric)
  - We'll be using the two-tailed test for the practical

Don't Ignore Ties

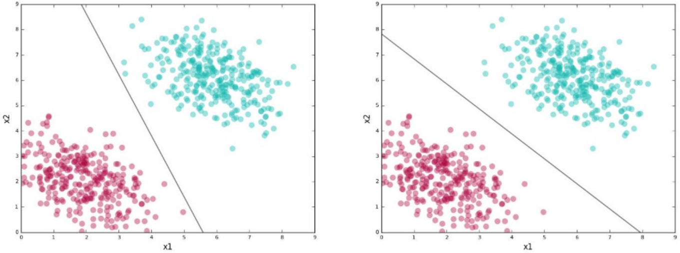
- When comparing two systems in classification tasks, it is common for a large number of ties to occur
- Disregarding ties will tend to affect a study's statistical power
- Here we will treat ties by adding 0.5 events to the positive and 0.5 events to the negative side (and round up at the end)
- Sign test implementation details in instructions handout

New: Support Vector Machines

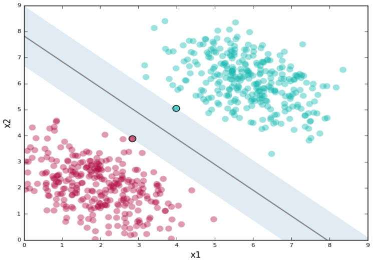
- SVM is a generalisation of simple maximal margin classifier and support vector classifier
- Both of these require that classes are separable by linear boundary.
- Support Vector Machines can use non-linear boundaries (kernels)
- Further extensions lead to multi-class SVMs

Hyperplanes and support vectors

- A hyperplane in p-dimensions is a flat $p-1$-dimensional affine subspace
- Compute the distance between data points and various hyperplanes
- Select the one that creates the largest margin (best separation) between the two classes.
- Support vectors are data points lying on the margin.
- The size of the margin = the SVM's confidence in the



Support Vector Machines



- SVM-Light: implementation of Support Vector Machines (Joachims, 1999)
  - Easy to use (just download the binaries and convert your features to SVM-Light format)

New: Stemming

- Pang et al. (2002) test whether stemming works.
- Please replicate.
- Use the Porter stemmer.

New: Bigrams

- Pang et al. (2002) test unigrams, bigrams and trigrams.
- Trigrams don't help (why not?)
- Please replicate unigrams and bigrams.

Questions?