Statistical methods in NLP
Evaluating and comparing classifiers

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overview

overview of the second programming assignment

significance testing for the accuracy

comparing two classifiers

the second programming assignment

- in the previous assignment, you implemented a classifier
- you will now make a more thorough analysis of how well it works

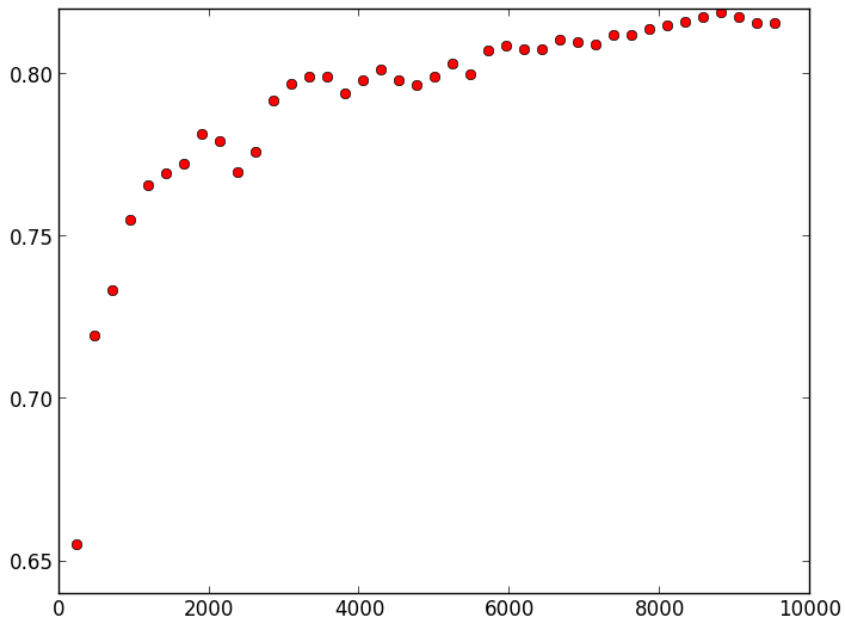
estimating the accuracy, and precision/recall

- warmup: compute the accuracy (as in last assignment)
- also: precision and recall for the positive class

$$P = \frac{\text{nbr. correct pos}}{\text{nbr. guessed pos}} \qquad R = \frac{\text{nbr. correct pos}}{\text{nbr. pos in the test set}}$$

learning curve

- set aside a test set
- use training sets of different sizes
- estimate the accuracy for each training set size
- plot the result



confidence interval for the accuracy

- you can use the recipe that we used previously:

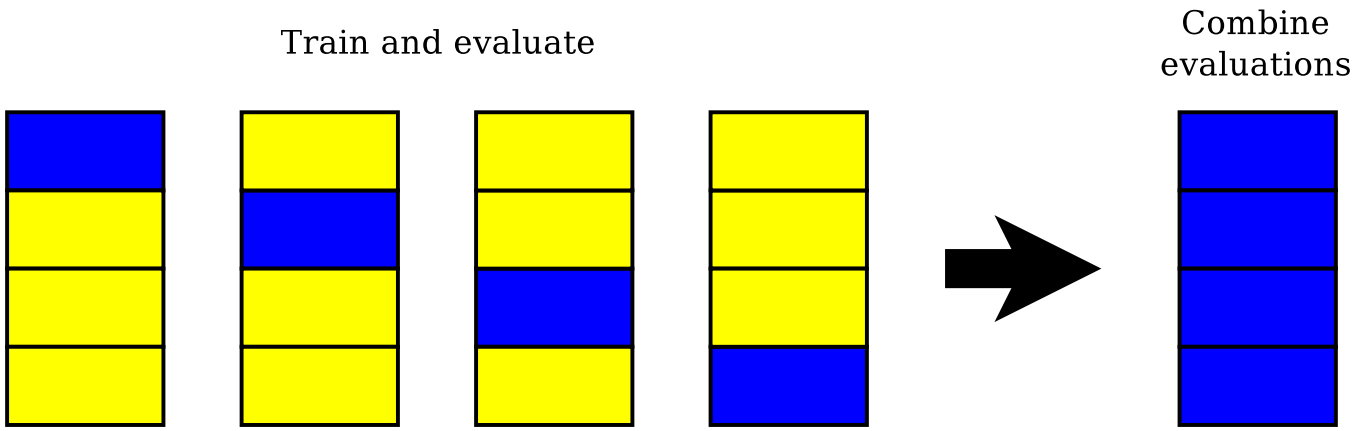
```
acc_mle = n_correct / n

rv = scipy.stats.binom(n, acc_mle)

acc_low = rv.ppf(0.025) / n
acc_high = rv.ppf(0.975) / n
```

evaluation with cross-validation

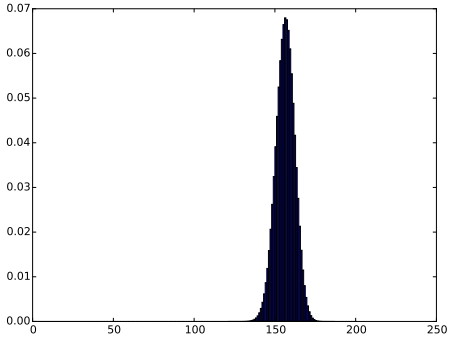
- we've discussed that the uncertainty of the estimate depends on the test set size
- **cross-validation** allows us to use more data for testing
- idea:
  - split into N parts of equal size (**folds**)
  - each fold is once a test set; then the others are the training set
  - evaluate on each fold and combine evaluations

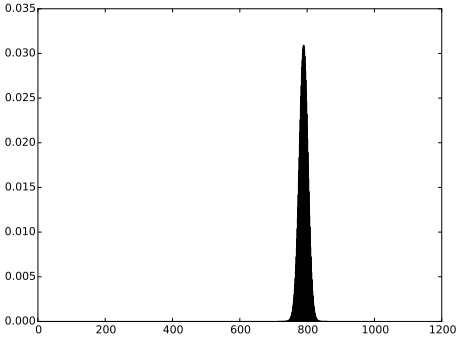


- recompute the accuracy and its confidence interval

cross-validation example

- our corpus consists of 1,000 documents, we split it into five 200-document pieces
- we use part 1 for testing and train on parts 2, 3, 4, 5; we classify 156 instances correctly
- for the other parts, the number of correct guesses is 163, 149, 164, and 157, respectively
- if we only consider part 1, then the CI is 0.720–0.835
- if we consider all parts, then the CI is 0.763–0.814





statistical significance testing for the accuracy

- in the last two tasks, you will consider two questions:
  - how sure are we that the true accuracy is better than 0.80?
  - how sure are we that classifier A is better than classifier B?
- we'll see recipes that can be used in these two scenarios
- these recipes work when we can assume that the "tests" (e.g. documents) are independent
  - fine for evaluations of classifiers, but not for more complex linguistic evaluations (tagging, parsing, translation, etc)

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comparing the accuracy to some given value

- my boss has told me to build a classifier with an accuracy of at least 0.70
- my NB classifier made 40 correct predictions out of 50
  - so the MLE of the accuracy is 0.80
- based on this experiment, how certain can I be that the accuracy is really greater than 0.70?
- if the true accuracy is 0.70, **how unusual is our outcome**?

statistical hypothesis testing

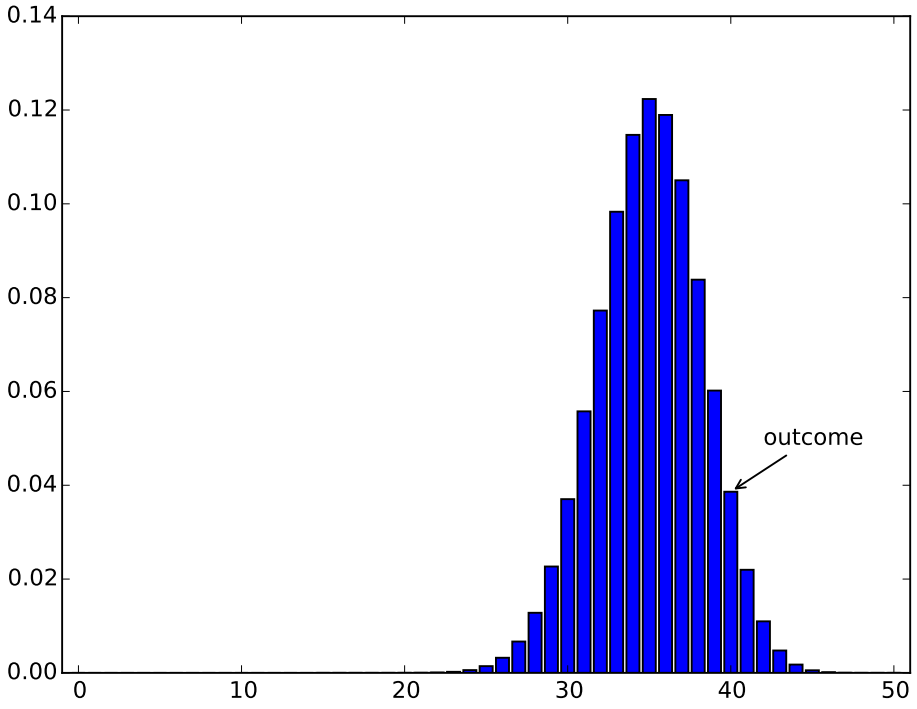
- we assume a **null hypothesis** and then see how **unusual** our outcome is
  - the null hypothesis is typically "boring": the true accuracy is equal to 0.7
- the "unusualness" is measured by the ***p*-value**
  - if the null hypothesis is true, how likely are we to see an outcome as unusual as the one we got?
- we typically want our p-values to be less than 0.05

the exact binomial test

- the **exact binomial test** is used when comparing an estimated probability (e.g. the accuracy) to some fixed value
  - 40 correct guesses out of 50
  - is the true accuracy really different from 0.70?
- if the null hypothesis is true, then this experiment corresponds to a binomially distributed r.v. with parameters 50 and 0.70
- we compute the p-value as the probability of getting an outcome at least as unusual as 40

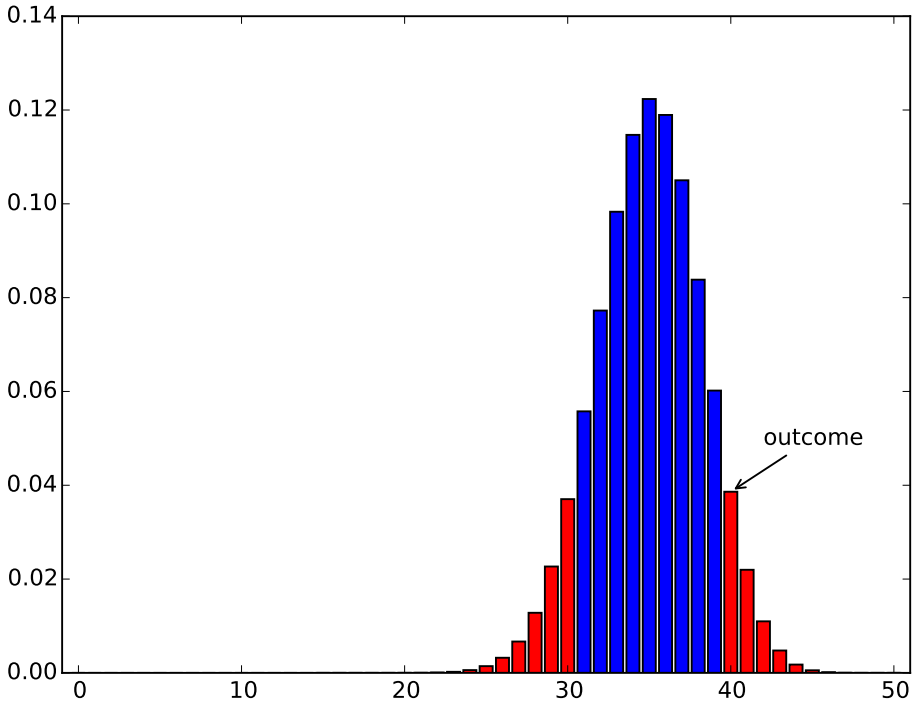
example

- 40 correct guesses out of 50
- is the true accuracy really different from 0.70?



example

- 40 correct guesses out of 50
- is the true accuracy really different from 0.70?



- the p-value is 0.16, so it seems we can't be sure!

implementing the exact binomial test in Scipy

- assume we made `x` correct guesses out of `n`
- is the accuracy significantly different from `test_acc`?
- the *p*-value is the sum of the probabilities of the outcomes that are at least as "unusual" as `x`:

```
import scipy.stats

def exact_binom_test(x, n, test_acc):
    rv = scipy.stats.binom(n, test_acc)
    p_x = rv.pmf(x)
    p_value = 0
    for i in range(0, n+1):
        p_i = rv.pmf(i)
        if p_i <= p_x:
            p_value += p_i
    return p_value
```

- actually, we don't have to implement it since there is a function `scipy.stats.binom_test` that does exactly this!

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- I'm comparing a Naive Bayes and a perceptron classifier
- we evaluate them on the **same test set**
- the NB classifier had 186 correct out of 312 guesses
- ...and the perceptron had 164 correct guesses
- so the ML estimates of the accuracies are 0.60 and 0.53, respectively
- but can I be certain that the NB classifier is really better?

contingency table

- we make a table that compares the errors of the two classifiers:

	NB correct	NB incorrect
perc correct	A = 125	**B = 39**
perc incorrect	**C = 61**	D = 87

- if NB is about as good as the perceptron, the B and C values should be similar
  - conversely if they are really different, B and C should differ
- are these B and C value **unusual**?

McNemar's test

- in **McNemar's test**, we model the discrepancies (the B and C values)

	NB correct	NB incorrect
perc correct	A = 125	**B = 39**
perc incorrect	**C = 61**	D = 87

- there are a number of variants of this test
  - the original formulation:
    Quinn McNemar (1947). *Note on the sampling error of the difference between correlated proportions or percentages*, Psychometrika 12:153-157.
- our version builds on the exact binomial test that we saw before

McNemar's test (continued)

	NB correct	NB incorrect
perc correct	A = 125	**B = 39**
perc incorrect	**C = 61**	D = 87

- the number of discrepancies is B+C
- how are the discrepancies distributed?
  - if the two systems are equivalent, the discrepancies should be more or less evenly spread into the B and C boxes
  - it can be shown that B would be a binomial random variable with parameters B+C and 0.5
- so we can find the *p*-value (the "unusualness") like this:

```
p_value = scipy.stats.binom_test(B, B+C, 0.5)
```

- in this case it is 0.035, so it seems that NB is really better

next weeks

- lecture next Tuesday in L308:
  - HMM tagging and Viterbi recap
  - confidence intervals and comparisons for taggers
- next assignment: implementing a HMM tagger