How to automatically label text?

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Question for the day

"How to predict a label for given text?"

Agenda

- Classification problem
- Naive Bayes
- Logistic regression
- Training/test setup
- Evaluation metrics

Text classification

- Input: document (e.g., email)
- Output: label (e.g., spam/ham)

Text classification problems

Task	x	y
Language ID	text	{english, mandarin, hindi, …}
spam classification	email	{spam, ham}
party affiliation	speech	{republican, democrat}
sentiment analysis	text	{positive, negative, mixed, neutral}
music genre	lyric	{rock, pop, jazz, rap,…}

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  - $x \in \mathcal{X}$ (e.g., set of emails)
- y is the desired label (e.g., spam)
  - $y \in \mathcal{Y}$ (e.g., {spam, ham})
- $y = h(x)$
  - h maps instances to labels

Classification

- True h is unknown so find $\hat{h}$ that's a closest approximation

Supervised learning

- Learn $\hat{h}$ from training data given in the form of several $<x, y>$ pairs

Naive Bayes

- One simple yet effective classification method is Naive Bayes
  - Similar to LDA, it's a generative model
  - We'll represent input text as a bag of words vector

Naive Bayes

- Naive conditional independence assumption

$$P(x_i \mid x_{i-1}, x_{i-2}, \ldots, y) = P(x_i \mid y)$$

- Given the category, the words (features) are independent of each other
- Under naive Bayes, P(“prince”|spam) = P(“prince”|spam, “kenyan”)

Now we can rewrite the posterior probability as:

$$\approx P(y)\ P(x_1|y)\ P(x_2|y)\ P(x_3|y)\ldots P(x_n|y)$$

$$= P(y) \prod_{i=1}^{n} P(x_i|y)$$

This is tractable!

Now we can rewrite the posterior probability as:

$$P(y \mid x_1, x_2, \ldots, x_n) \propto P(y)\ P(x_1 \mid y)\ P(x_2 \mid x_1, y)\ P(x_3 \mid x_2, x_1, y) \ldots P(x_n \mid x_{n-1}, \ldots, x_1, y)$$

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$$= P(y) \prod_{i=1}^{n} P(x_i \mid y)$$

This is tractable!

We can estimate these probabilities by simply counting the instances in training data

$$P(y = spam) = \frac{\#\text{samples labeled spam}}{\#\text{ samples}}$$

$$P(\text{"kenyan"} \mid \text{spam}) = \frac{\#\text{samples labeled spam and contain "kenyan"}}{\#\text{samples labeled spam}}$$

Picking the label

- Once you estimate the probabilities from training data, you can pick the label that maximizes the posterior

$$P(y = \text{spam} \mid \text{text}) > P(y = \text{ham} \mid \text{text})$$ Spam

otherwise Ham

$$\log P(y \mid x) \propto \log P(y) + \sum_{i=1}^{N} \log P(x_i \mid y)$$

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Naive Bayes is a linear model

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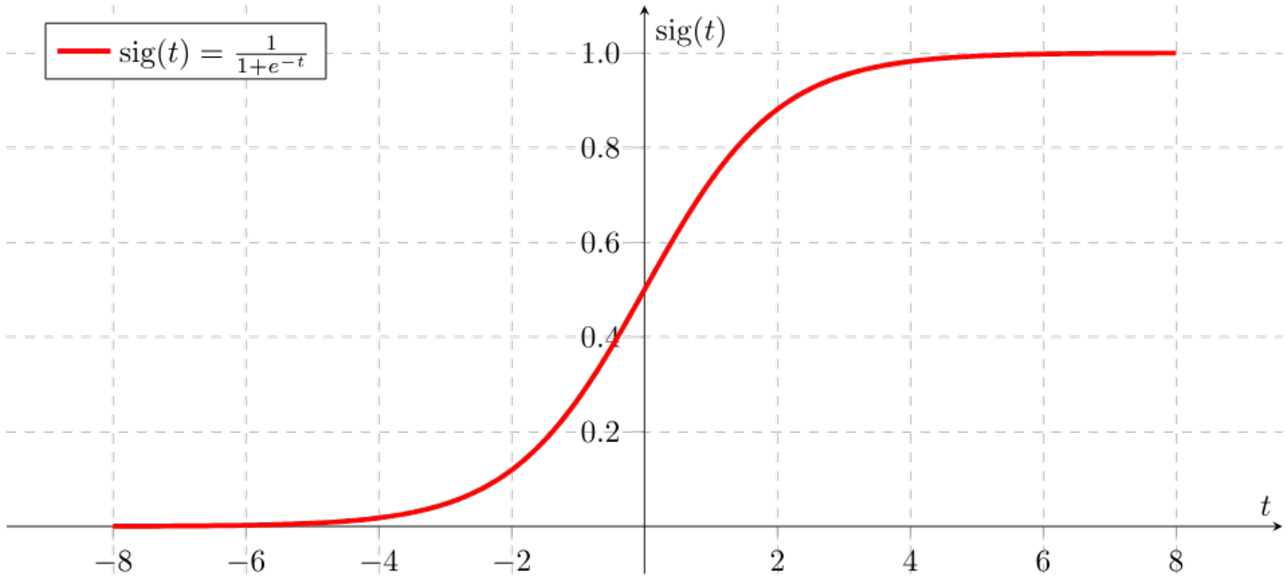
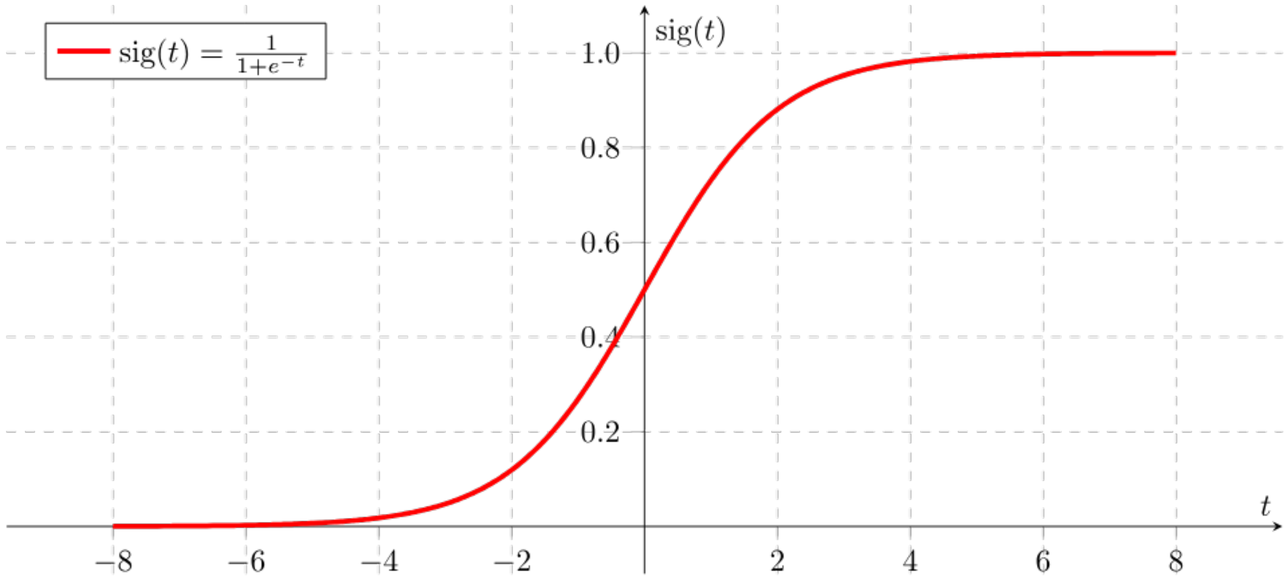


Logistic Regression

In logistic regression, we directly model the conditional probability of the label given the text

$$P(y \mid x) = \text{sig}(w^T f(x))$$



This is highly flexible because we can encode any type of features that we think could be useful

Learning

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- Unlike Naive Bayes, no closed form solution
- Weights are learned by optimizing some criterion on training data

Generalized classification

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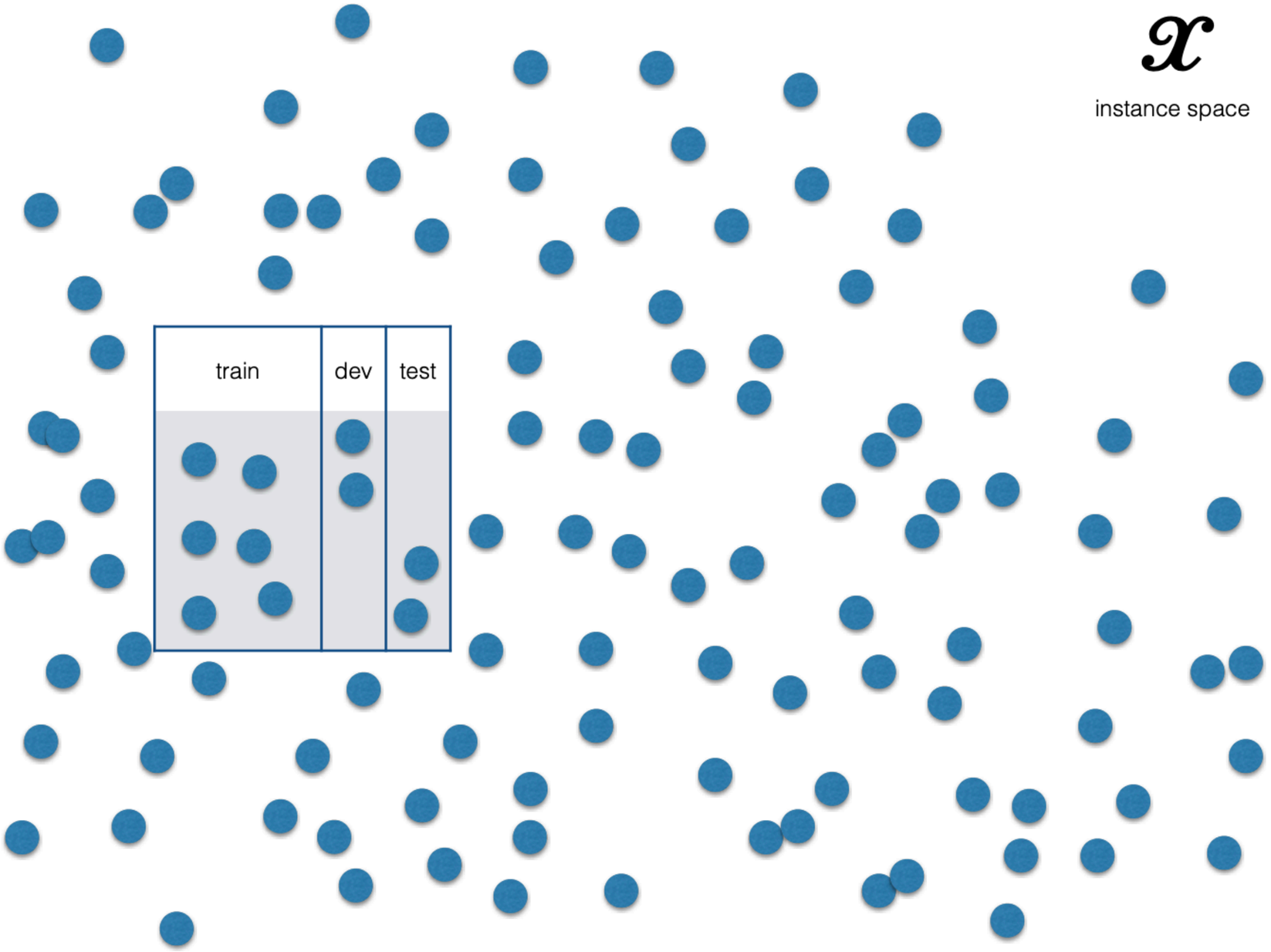
Generalized classification

- Alternatives to linear models also exist.
- $P(y|x) = \text{sig}(g(f(x)))$ g could be a neural network
- For multi-class classification, $P(y|x) = \text{softmax}(g(f(x)))$

Generalized forecasting

Generalized forecasting

- Same model can be used to predict continuous values
- $y = g(f(x))$
- If g is a linear function, this is linear regression



Slide from David Bamman

Experiment design

- Training set is to estimate parameters of the model
- Development set is to perform model selection
- Test set for evaluation

Experiment design

- Typically, we use 80% data for training, 10% for model selection and 10% for evaluation
- One should be careful never to use to development or test data to do estimation

Feature function

Feature function

- Feature function transforms text into a feature vector
  - e.g. text -> counts vector
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Regularization

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- The value of the penalty is controlled by a hyper parameter which should be tuned on the development set

How do we know if our learned classifier is good?

	1	2	3	4	5	6	7	8	9	10
y	spam	spam	spam	spam	spam	ham	ham	ham	ham	ham
yhat	spam	spam	ham	spam	spam	spam	ham	spam	ham	spam

	1	2	3	4	5	6	7	8	9	10
y	spam	spam	spam	spam	spam	ham	ham	ham	ham	ham
yhat	spam	spam	ham	spam	spam	spam	ham	spam	ham	spam

Confusion Matrix

Confusion Matrix

Predicted \ Observed	y=spam	y=ham
yhat = spam	4	3
yhat=ham	1	2

Confusion Matrix

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Predicted \ Observed	y=spam	y=ham
yhat = spam	True positives	False positives
yhat=ham	False negatives	True negatives

Confusion Matrix

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- N = True positives + True negatives + False positives + False negatives

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Accuracy

$$\frac{\text{True positives} + \text{True negatives}}{N}$$

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Accuracy

$$\frac{\text{True positives} + \text{True negatives}}{N}$$

Predicted\Observed	y=spam	y=ham
yhat = spam	True positives	False positives
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- We want the accuracy of the classifier to be high

Precision

Precision

Predicted\Observed	y=spam	y=ham
yhat = spam	True positives	False positives
yhat=ham	False negatives	True negatives

Precision

$$\frac{\text{True positives}}{\text{True positives + False positives}}$$

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Precision

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- We want number of false positives to be low and precision to be high

Recall

Recall

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Recall

$$\frac{\text{True positives}}{\text{True positives + False negatives}}$$

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Recall

$$\frac{\text{True positives}}{\text{True positives + False negatives}}$$

Predicted\Observed	y=spam	y=ham
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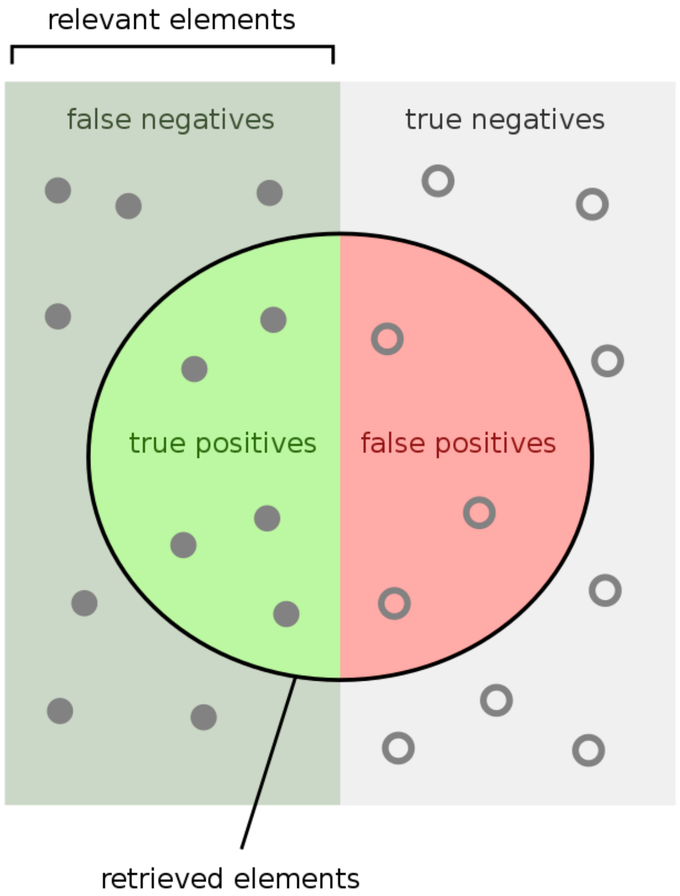
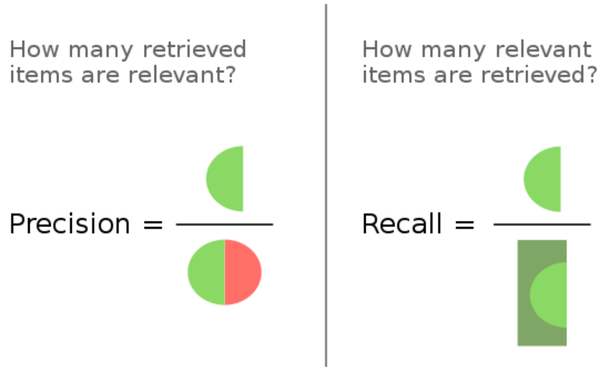
- We want number of false negatives to be low and recall to be high

Precision and Recall





Source: Wikipedia

F1

- We can combine precision and recall into a single metric by taking the harmonic mean of the two quantities.

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

In class

- Text classification demo