Advanced Text Analysis for Business (IDS-566)

Lecture 4

Feb 16, 2018

Course Overview

- Instructor
  - Ehsan M. Ardehaly PhD, ehsan@uic.edu
  - Office hours: 4:45 - 5:45 pm F, BLC L270
  - Teacher assistant: 4:00 - 5:00 pm W, BLC L270
- Objectives:
  - Text mining
  - Applications for business decisions
  - Study of machine learning concepts
  - Design and implementation of text mining approaches

Assignments-2

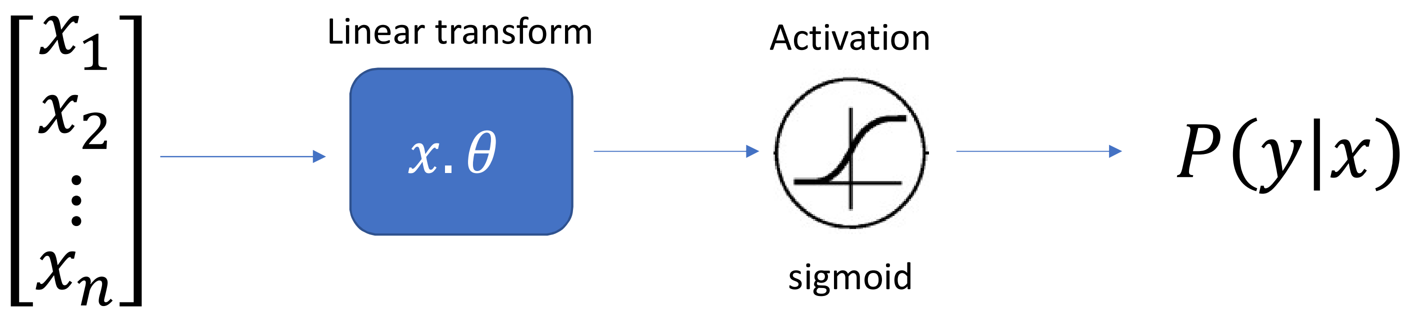
- Grade: 20%
- Sentiment analysis
- Due date: 2/25/2018

- Submission:
    - Notebook (code + analysis) → PDF
    - Word document with code as an appendix → PDF

Agenda

Logistic regression	• MLE, cost function, regularization, multi-class
Gradient descent:	• Solving logistic regression
Metrics:	• Confusion matrix, precision, recall, F1
Applications:	• Sentiment analysis, demographic classification

Logistic Regression



Likelihood

- Conditional probability of i-th sample to be positive:
  - $P(y_i = 1|X_i) = \sigma(X_i.\theta)$ ← sigmoid function
- Conditional probability of i-th sample to be negative:
  - $P(y_i = 0|X_i) = 1 - \sigma(X_i.\theta)$
- Likelihood:
  - $L(X;\theta) = \prod_i P(y_i = 1|X_i)^{y_i} P(y_i = 0|X_i)^{1-y_i}$

Likelihood

- $L(X;\theta) = \prod_i P(y_i = 1|X_i)^{y_i} P(y_i = 0|X_i)^{1-y_i}$
- Example:
- Predicted probabilities for positive samples: .9, .8, .2
- Predicted probabilities for negative samples: .6, .1
- $L = (.9^1 \times .1^0)(.8^1 \times .2^0)(.2^1 \times .8^0)(.6^0 \times .4^1)(.1^0 \times .9^1)$
- $L = .9 \times .8 \times .2 \times .4 \times .9 = 0.05184$

Maximum Likelihood Estimation (MLE)

- Find θ that maximizes likelihood:
  - $L(X;\theta) = \prod_i P(y_i = 1|X_i)^{y_i} P(y_i = 0|X_i)^{1-y_i}$
- Or maximize log-likelihood:
  - $\mathrm{l}(X;\theta) = \sum_i (y_i \log P(y_i = 1|X_i) + (1 - y_i) \log P(y_i = 0|X_i))$
  - $\mathrm{l}(X;\theta) = \sum_i (y_i \log \sigma(X_i.\theta) + (1 - y_i) \log(1 - \sigma(X_i.\theta))$

Cost function

- Maximize log-likelihood
- Or
- Minimize negative log-likelihood (cost function):
- $\mathrm{J}(\theta) = -\sum_i (y_i \log \sigma(X_i . \theta) + (1 - y_i) \log(1 - \sigma(X_i . \theta))$

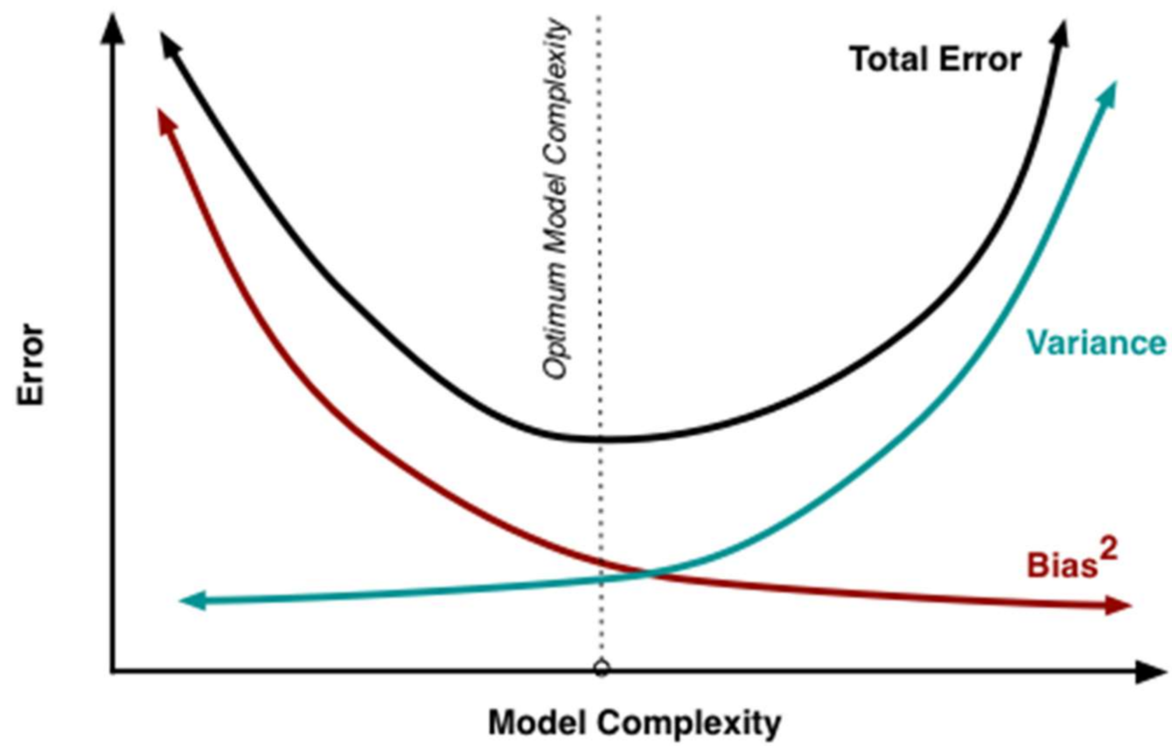
- Example:
    - $L = .9 \times .8 \times .2 \times .4 \times .9 = 0.05184$
    - $l = \log .05184 = -2.96$
    - $J = 2.96$

Training logistic regression

- Creating the cost function:
  - Negative log likelihood
  - $J(\theta) = -l(\theta) = -\sum_i (y_i \log \sigma(X_i . \theta) + (1 - y_i) \log(1 - \sigma(X_i . \theta))$

- Find θ which minimizes the cost function:
  - $\theta = \underset{\theta}{\mathrm{Argmin}}\, J(\theta)$

Bias vs. Variance



How to control the variance?

- Adding the regularization term.
- Penalize the cost function for high variation.
- No impact on hypothesis function.

L2 regularization

- Penalize the magnitude of model parameters:
  - $\|\theta\|_2^2 = \sum_{i=1}^{n} \theta_i^2$
  - $\mathrm{J}(\theta) = -l(\theta) + \lambda\|\theta\|_2^2$

- Regularization strength:
  - Higher λ → Low variation

  - Lower λ → High variation

L1 regularization

- Penalize the absolute deviation of parameters:
  - $\|\theta\|_1 = \sum_{i=1}^{n} |\theta_i|$
  - $\mathrm{J}(\theta) = -l(\theta) + \lambda\|\theta\|_1$

- Regularization strength:
  - Higher λ → Low variation
  - Lower λ → High variation

Elastic net regularization

- Take advantage of both regularization
- Combine both L1 and L2:
  - $\mathrm{J}(\theta) = -l(\theta) + \alpha\|\theta\|_1 + \beta\|\theta\|_2^2$
- Hard to tune.

L1 vs L2

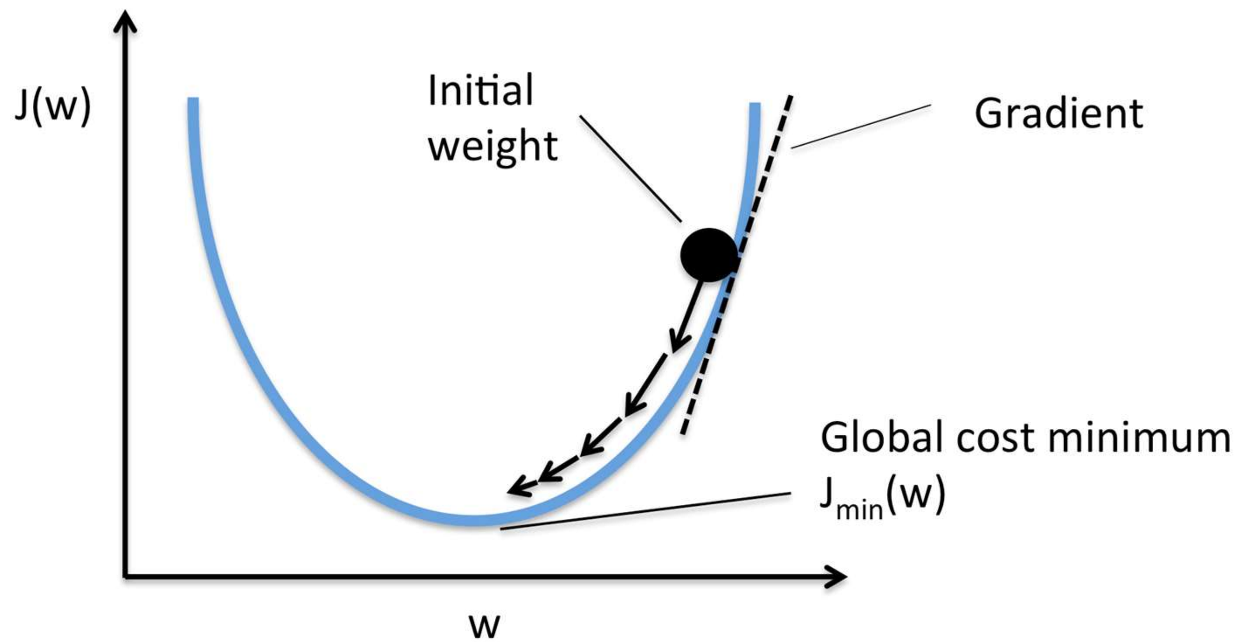
- L1:
  - Shrinks less important features.
  - Good for feature selection.

- L2:
  - Often have better result.

Gradient descent algorithm

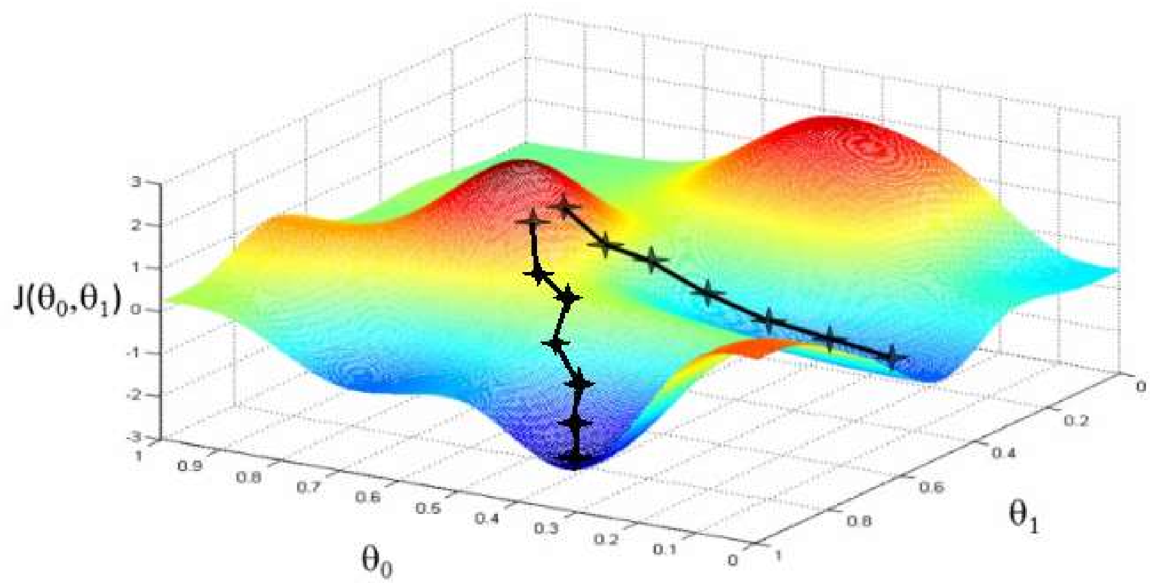
- An iterative algorithm
- Finding the minimum of a function:
  - Local minimum ← non-convex function
  - Global minimum ← convex function
- Starts with a random initialization.
- Takes step to the negative of the gradient.

Convex-GD



https://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/

Non-convex GD



http://blog.datumbox.com/tuning-the-learning-rate-in-gradient-descent/

Gradient Descent

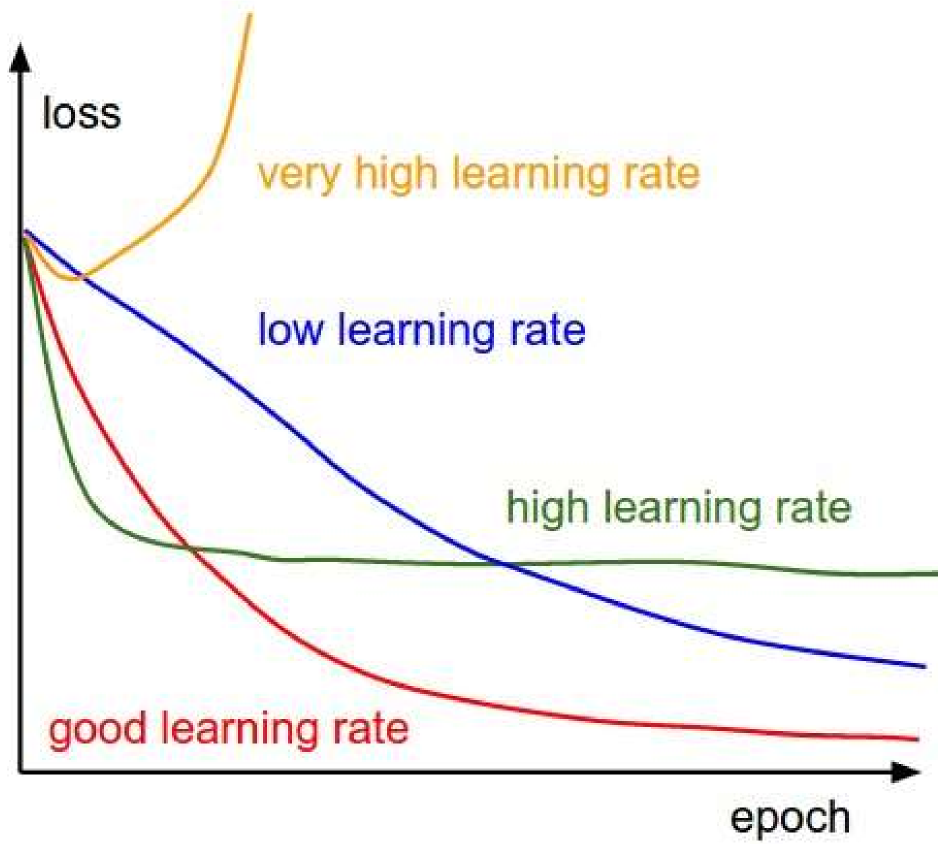
- Input:
  - Lost function: $J(\theta)$
  - Learning rate: η

- Initialize with random small parameters: θ_0
- Descent to local minimum:
  - $\theta_{n+1} = \theta_n - \eta \nabla J(\theta_n)$
  - Stopping condition

Gradient

- Gradient is a vector (with size of parameters)
- Partial deviation:
  - $\nabla J_i = \frac{\partial J}{\partial \theta_i}$

Learning rate



Gradient descent for Logistic regression

- $\mathrm{J}(\theta) = -\sum_i (y_i \log \sigma(X_i.\theta) + (1 - y_i) \log(1 - \sigma(X_i.\theta))$
- Gradient:
  - $\nabla J(\theta) = \sum_i X_i(\sigma(X_i.\theta) - y_i)$
- Gradient descent:
  - $\theta_{n+1} = \theta_n - \eta \sum_i X_i(\sigma(X_i.\theta_n) - y_i)$

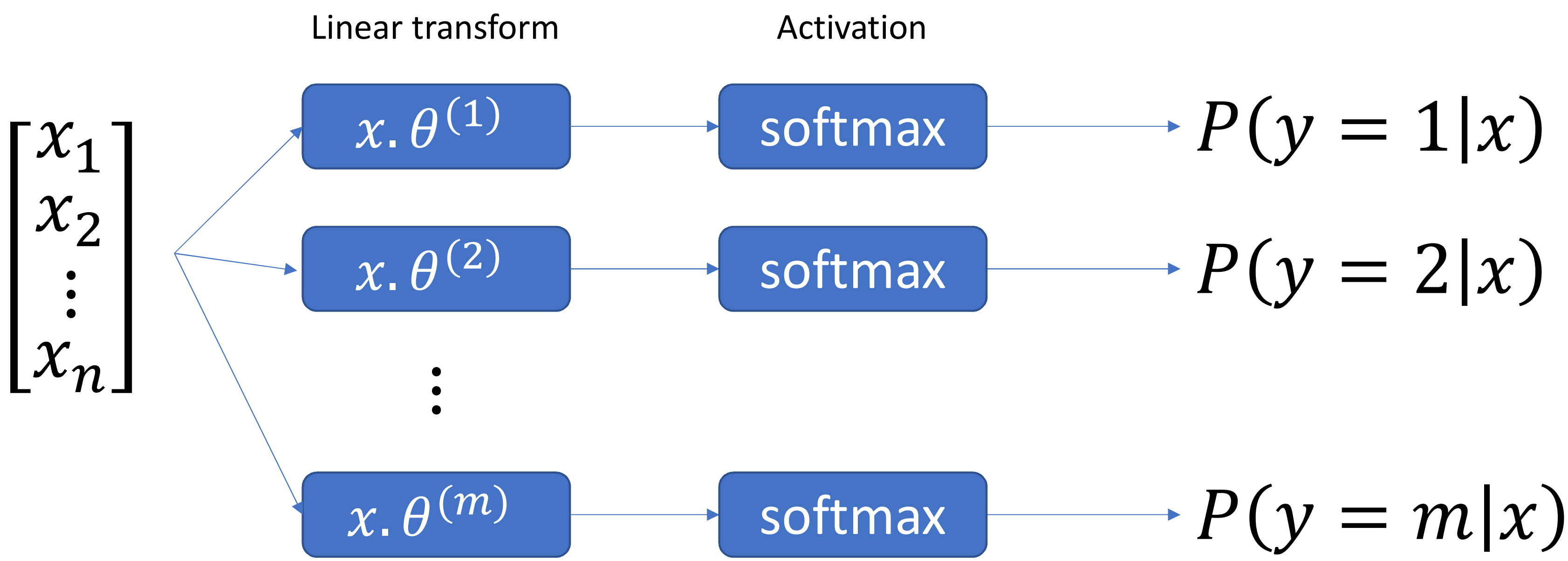
Multi-class logistic regression

- Parameters for each class: (m classes)
  - $\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(m)}$
- Hypothesis:
  - Softmax function
  - $P(y_i = k | X_i) = \frac{\exp(X_i . \theta^{(k)})}{\sum_{j=1}^{m} \exp(X_i . \theta^{(j)})}$

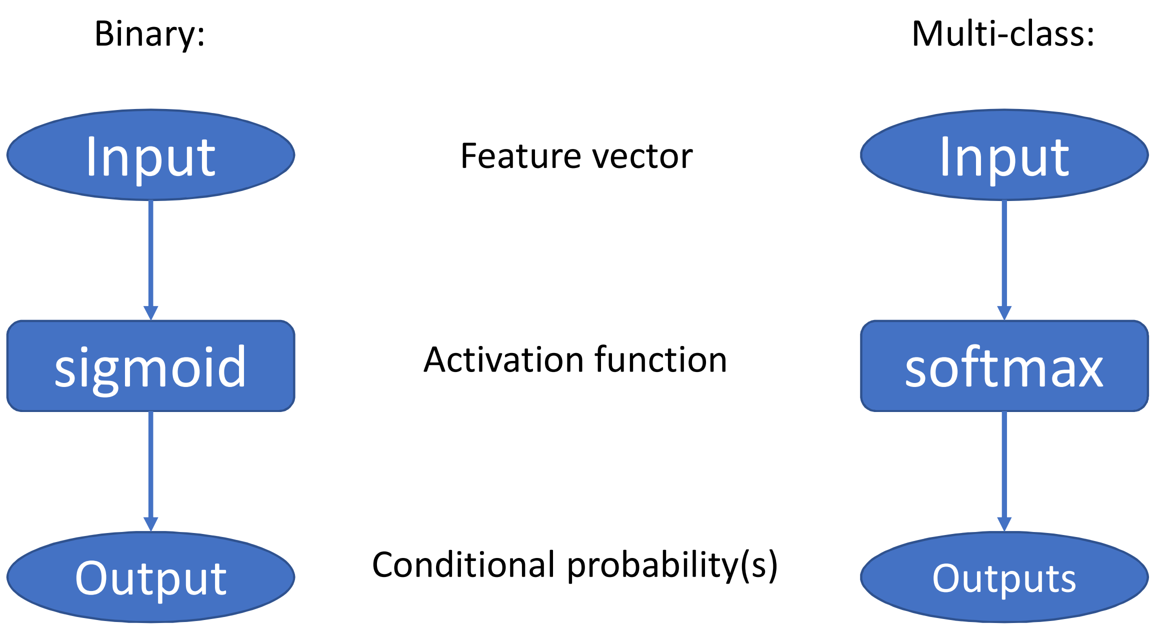
Multi-class logistic regression

- Softmax hypothesis:
  - $P(y_i = k|X_i) = \frac{\exp(X_i.\theta^{(k)})}{\sum_{j=1}^{m} \exp(X_i.\theta^{(j)})}$
- How to solve:
  - Create the lost function as negative log likelihood.
  - Use gradient descent algorithm

Multi-class logistic regression



Binary vs. Multi-class



Analyzing classifier result

- Confusion matrix
- Metrics
- Error analysis

Confusion Matrix

	Predicted: No	Predicted: Yes
Actual: No	300	80
Actual: Yes	20	600

Confusion Matrix

	Predicted: No	Predicted: Yes
Actual: No	TN = 300	FP = 80
Actual: Yes	FN = 20	TP = 600

Accuracy

	Predicted: No	Predicted: Yes
Actual: No	TN = 300	FP = 80
Actual: Yes	FN = 20	TP = 600

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} = \frac{300 + 600}{300 + 600 + 20 + 80} = .9$$

Accuracy: Rate of corrected prediction

Precision

	Predicted: No	Predicted: Yes
Actual: No	TN = 300	FP = 80
Actual: Yes	FN = 20	TP = 600

$$Precision = \frac{TP}{TP + FP} = \frac{600}{600 + 80} = .882$$

Precision: How many selected documents are relevant?

Recall

	Predicted: No	Predicted: Yes
Actual: No	TN = 300	FP = 80
Actual: Yes	FN = 20	TP = 600

$$Recall = \frac{TP}{TP + FN} = \frac{600}{600 + 20} = .968$$

Recall: how many relevant documents are selected?

F1

	Predicted: No	Predicted: Yes
Actual: No	TN = 300	FP = 80
Actual: Yes	FN = 20	TP = 600

$$F1 = 2\frac{Prec.Recall}{Prec + Recall} = 2\frac{.882 \times .968}{.882 + .968} = .923$$

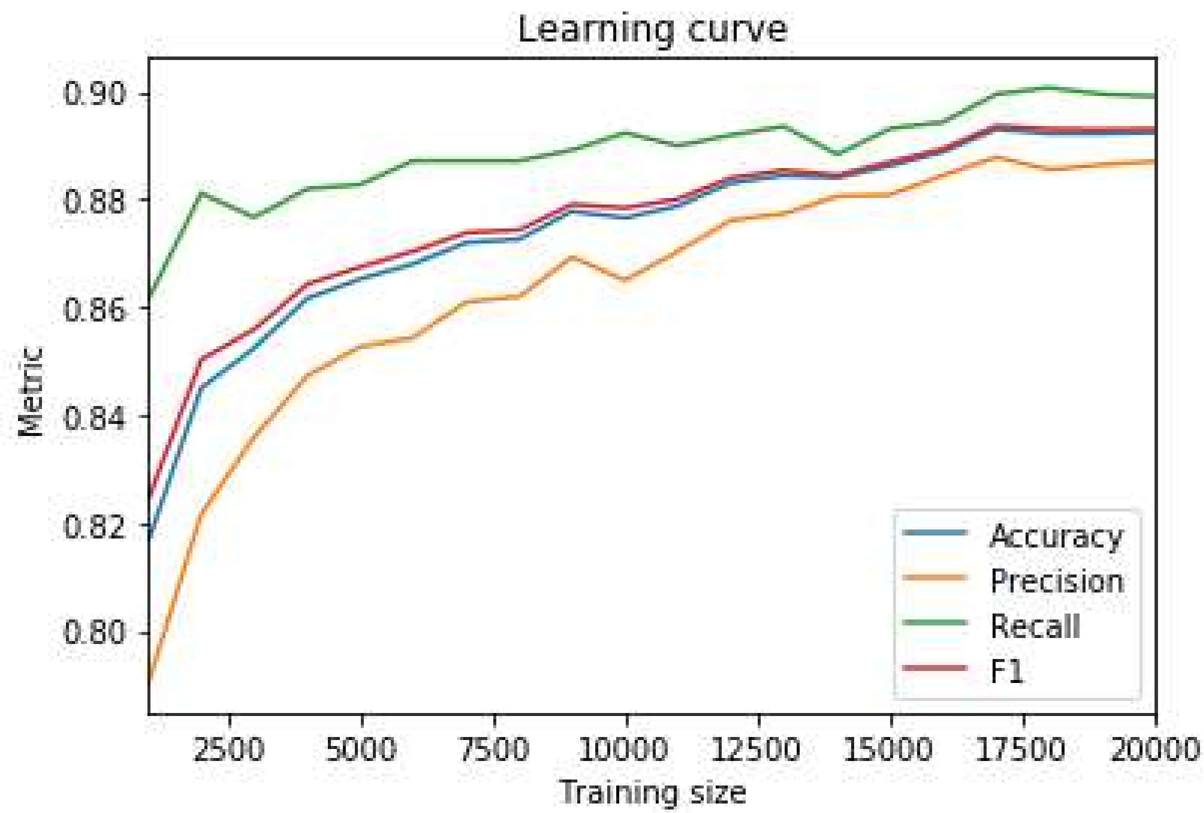
F1: The harmonic average of precision and recall

False Positive Rate (FPR)

	Predicted: No	Predicted: Yes
Actual: No	TN = 300	FP = 80
Actual: Yes	FN = 20	TP = 600

$$FPR = \frac{FP}{FP + TN} = \frac{80}{80 + 300} = .211$$

Learning Curve



Sentiment analysis models

Using	Using
Lexicon • Requires a dictionary	**Text classification** • Requires training data

Demographic classification

- Classifying demographic attributes from textual activities:
    - Gender
    - Race
    - Age
    - Income

Applications

- Marketing
- Public health
- Opinion mining