# University of Toronto

Neural Networks for Machine Learning



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## Contents

1	Introduction	1
2	The Perceptron learning procedure	1
3	The backpropagation learning proceedure	1
4	Learning feature vectors for words	1
5	Object recognition with neural nets 5.1 Why object recognition is difficult 5.2 Achieving viewpoint invariance The invariant feature approach The judicious normalization approach The brute force normalization approach	1 1 1 2 2
6	Optimization: How to make the learning go faster	2
7	Recurrent neural networks	2
8	More recurrent neural networks	2
9	Ways to make neural networks generalize better	2

10 Combining multiple neural networks to improve generalization	2
11 Hopfield nets and Boltzmann machines	2
12 Restricted Boltzmann machines (RBMs)	2
13 Stacking RBMs to make Deep Belief Nets	2
14 Deep neural nets with generative pre-training	2
15 Modeling hierarchical structure with neural nets	2
16 Recent applications of deep neural nets	2

#### Abstract

Todo

- 1 Introduction
- 2 The Perceptron learning procedure
- 3 The backpropagation learning procedure
- 4 Learning feature vectors for words
- 5 Object recognition with neural nets
- 5.1 Why object recognition is difficult
  - Things that make it hard to recognize objects:
    - **Segmentation:** Real scenes are cluttered with other objects
      - It's hard to tell which pieces go together as parts of the same object
      - Parts of an object can be hidden behind other objects
    - **Lighting:** The intensities of the pixels are determined as much by the lighting as by the objects
    - **Deformation:** Objects can deform in a variety of non-affine ways:
      - eg. a hand-written 2 can have a large loop or just a cusp
    - Affordances: Object classes are often defined by how the are used
    - Viewpoint: Changes in viewpoint cause changes in images that standard learning methods cannot cope with

### 5.2 Achieving viewpoint invariance

- Several approaches:
  - Use redundant invariant features
  - Put a box around the object and use normalized pixels
  - Use replicated features with pooling. This is called "convolution neural nets"
  - Use a hierarchy of parts that have explicit poses relative to the camera

#### The invariant feature approach

- Extract a large, redudant set of features that are invariant under transformations
- With enough invariant features, there is only one way to assemble them into an object
- But for recognition, we must avoid forming features from parts of different objects

#### The judicious normalization approach

- Put a box around the object and use it as a coordinate frame for a set of normlized pixels
  - This solves the dimension-hopping problem. If we choose the box correctly, the same part of an object always occurs on the same normalized pixels
  - The box can provide invariance to many degrees of freedom: translation, rotation, scale, shear, stretch, etc.
- Chooosing the box is difficult because of: segmetration erros, occlusion, unusual orientations
- We need to recognize the shape to get the box right (chicken and egg dilema)

#### The brute force normalization approach

- When training the recognizer, use well-segmented, upright images to fit the correct box
- At test time try all possble boxes in a range of position and scales
  - This approach is widely used for detecting upright things like faces and house numbers in unsegmented images
  - It is much more efficient if the recognizer can cope with some variation in position and scale so that we can use a coarse grid when trying all possible boxes
- 6 Optimization: How to make the learning go faster
- 7 Recurrent neural networks
- 8 More recurrent neural networks
- 9 Ways to make neural networks generalize better
- 10 Combining multiple neural networks to improve generalization
- 11 Hopfield nets and Boltzmann machines
- 12 Restricted Boltzmann machines (RBMs)
- 13 Stacking RBMs to make Deep Belief Nets
- 14 Deep neural nets with generative pre-training
- 15 Modeling hierarchical structure with neural nets
- 16 Recent applications of deep neural nets