Lecture Notes for

Neural Networks and Machine Learning

ConceptNet Demo

Intro to Transfer Learning

Logistics and Agenda

- Logistics
  - Spreadsheet for Presentations
- Agenda (Today is mostly review, will go quickly!)
  - ConceptNet (as needed)
  - Transfer Learning Overview
  - Transfer Learning in Deep Learning
  - Demo
- Next Time:
  - Transformers for Text and Vision
- Next Next Time
  - Self-Supervised Learning and Consistency Loss

How to Make a Racist AI without Really Trying

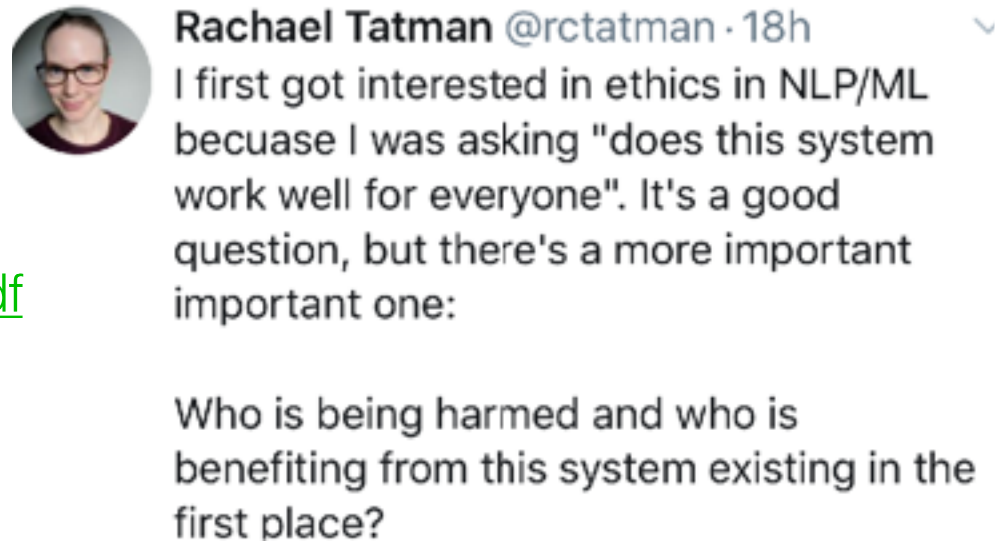
Robyn Speer, 2017

http://blog.conceptnet.io/posts/2017/how-to-make-a-racist-ai-without-really-trying/

Debiasing: Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Bolukbasi et al., NeurIPs 2016

https://arxiv.org/pdf/1607.06520.pdf



Rachael Tatman @rctatman · 18h

I first got interested in ethics in NLP/ML becuase I was asking "does this system work well for everyone". It's a good question, but there's a more important important one:

Who is being harmed and who is benefiting from this system existing in the first place?

ConceptNet 5.5: An Open Multilingual Graph of General Knowledge

Speer et al., AAAI 2017

https://arxiv.org/pdf/1612.03975.pdf

Lab One Town Hall

NLP Ethics Excuse Bingo

If I don't, someone else will	Who are you to decide?	Ethics is relative to culture	There are positive uses too
Ethics review is censorship	Science is neutral	Well, you flew to this conference	People are biased too
Negative outcomes are not predictable	Workers there are happy for $0.05	There are no alternatives	Don't slow down progress
You want to go back to candles?	Ethics review is US imperialism	The data was publicly accessible	Stop being political

Emily M. Bender & Karën Fort 2022

Transfer Learning Overview

Transfer Learning

- Transfer knowledge from a source prediction task to a target prediction task
  - without any regard for performing well on source task
- **Original**: Neural Information Processing 1995 (NeuRiPs)
  - Workshop on "Learning to Learn"
    - How to effectively retain and reuse previously learned knowledge
  - Originally used in Markov chain and Bayesian networks (keeping n-grams, *etc*.)
- **Key idea**: Humans can generalize what they learn to almost any domain, can we mimic this behavior with ML?
  - 🙄 Ugh, really ML people?

Ian Goodfellow’s Definition:

> *“Transfer learning refers to any situation where what has been learned in one setting is exploited to improve generalization in another setting.”*

Transfer Learning: Large Umbrella

- Appears under many associations in the literature:
  - Learning to learn / Life-long learning
  - Knowledge transfer / Inductive transfer
  - Multi-task learning
  - Knowledge consolidation
  - Context-sensitive learning
  - Knowledge-based inductive bias
  - Meta learning
  - Incremental learning
  - Cumulative learning
  - Domain adaptation

Precise Definition of Transfer Learning

$$X = x_1, x_2, \ldots x_N \in \mathscr{X}$$

$$Y = y_1, y_2, \ldots y_N \in \mathscr{Y}$$

$$\mathscr{D} = \{\mathscr{X}, p(X)\}$$

Domain **Feature Space** **Probability Observation**

$$\mathscr{T} = \{\mathscr{Y}, p(Y|X)\}$$

Task **Label Space** **Learned Probability**

- $\mathscr{D}$ Domain defines the features used and probability
- $\mathscr{X}$ is the space of all possible features
- $p(X)$ is probability of observing specific instances in $\mathscr{X}$
  - Typically **intractable** to calculate (generative)

- $\mathscr{T}$ Task is within a domain, defining labels and model
- $\mathscr{Y}$ is space of all possible labels
- $p(Y|X)$ probability of observing specific label given the specific feature:
  - **Not intractable** (discriminative)

Definition with Examples

$$X = x_1, x_2, \ldots x_N \in \mathscr{X}$$

$$Y = y_1, y_2, \ldots y_N \in \mathscr{Y}$$

$$\mathscr{D} = \{\mathscr{X}, p(X)\}$$

Domain | Feature Space | Probability Observation

$$\mathscr{T} = \{\mathscr{Y}, p(Y|X)\}$$

Task | Label Space | Learned Probability

- Image Pixels
- Sensor Readings
- Natural Language
- *Almost anything that we can represent as a feature*

- Object Classification
- Dolphin/Shark Classification
- Sentiment Analysis
- *Any labeled task for which we might be able to build a classifier*

Transfer Learning

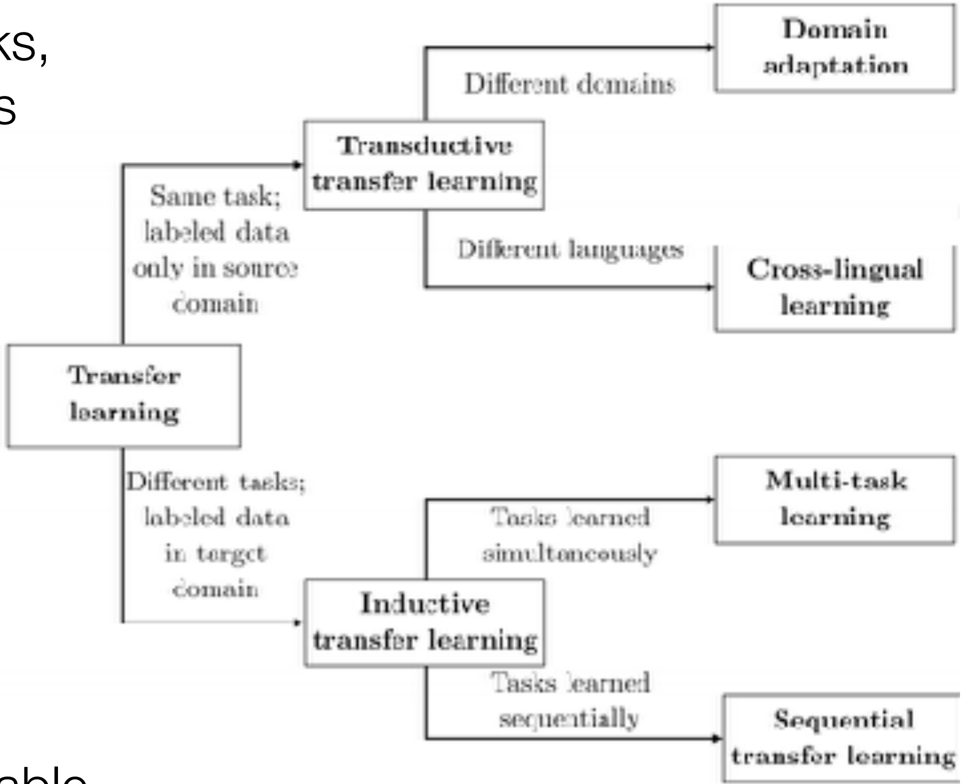
$$X = x_1, x_2, \ldots x_N \in \mathscr{X} \qquad Y = y_1, y_2, \ldots y_N \in \mathscr{Y}$$

$$\underbrace{\mathscr{D}}_{\text{Domain}} = \{\underbrace{\mathscr{X}}_{\text{Feature Space}}, \underbrace{p(X)}_{\text{Probability Observation}}\} \qquad \underbrace{\mathscr{T}}_{\text{Task}} = \{\underbrace{\mathscr{Y}}_{\text{Label Space}}, \underbrace{p(Y|X)}_{\text{Learned Probability}}\}$$

- Need to translate document **Source** to **Target** $\mathscr{T}_S \rightarrow \mathscr{T}_T$
- Variety of differences might be present. For example, in the context of document classification:
  - **Feature space**: different languages $\mathscr{X}_S \neq \mathscr{X}_T$
  - **Marginals**: same language, same label space, but differing topics $p(X_S) \neq p(X_T)$
  - **Conditional**: different label distributions or possibly different labels $p(Y_s|X_S) \neq p(Y_T|X_T)$

Categories of Transfer Learning

- **Inductive**: Same Domain, Different Task
  - Using pre-trained VGG as basis for classifying dolphins versus sharks, Style Transfer, sentiment analysis from Glove
- **Transductive**: Different (but related) Domains, Same Task
  - Place identification from RGB Images or LIDAR
- **Unsupervised Transfer**: Different Domains, Different Tasks
  - Learning to paint art and learning to be a surgeon
  - Not yet a field with much repeatable traction



Other categorizations

	Training	Testing
Transfer Learning	Task 1	Task 2
Multi-task Learning	Task 1 ··· Task N	Task 1 ··· Task N
Lifelong Learning	Task 1 ··· Task N	Task N+1

Lifelong Learning is a Grand AI Challenge: Humans can learn to ride a bike and use that to understand better about driving a car. Machine Learning in its current form is far from this capability. How can we move our siloed version of artificial intelligence closer to the process of human based learning? How can we accumulate knowledge from model to model?

Does biology of human learning hold any clues to success? How does a human learn to crawl? To talk? To ride a bike? What is a human's motivation to learn?

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Next Time:
More Transfer learning and Demo

Reading: None