# Machine Learning: CS 472/572 Introduction

### Instructor: Thien Huu Nguyen

Based on slides by Daniel Lowd, Vibhav Gogate, Pedro Domingos, and others.



## Logistics

- Instructor: Thien Huu Nguyen
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  - Office hours: Thursday (13:30-14:30), Friday: (13:30-14:30)
- Web: <a href="https://classes.cs.uoregon.edu/24S/cs472/">https://classes.cs.uoregon.edu/24S/cs472/</a>
- Discussion Board: Piazza (link on Canvas)
   Please use this for discussion!



## **Evaluation**

- 4 assignments (40%)
  - Some programming, some exercises
- One Midterm (30%)
  - 2/3rds of the way through
- One Project (30%)
  - Apply machine learning to a real problem of your choice (Recommended: Participate in a contest on Kaggle.com.)
  - Groups allowed (for undergrad students)
  - Code, written report



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# Kaggle

Active Competitions	+ Competition Name		▼ Reward	+ Teams	Deadline
All Competitions	R	National Data Science Bowl Predict ocean health, one plankton at a time	\$175,000	312	2 months
<b>17 found, 17 active</b> Q Search competitions	AXA	<b>Driver Telematics Analysis</b> Use telematic data to identify a driver signature	\$30,000	453	2 months
• All competitions • Enterable	Helping Santa's Helpers Jingle bells, Santa tells	\$20,000	439	2.1 days	
Status Active Completed	Avazu	<b>Click-Through Rate Prediction</b> Predict whether a mobile ad will be clicked	\$15,000	1203	35 days
Sponsor InClass (student competition)		BCI Challenge @ NER 2015 A spell on you if you cannot detect errors!	\$1,000	161	50 days
	U	Sentiment Analysis on Movie Reviews Classify the sentiment of sentences from the Rotten Tomatoes dataset	Knowledge	675	54 days
		<b>Finding Elo</b> Predict a chess player's FIDE Elo rating from one game	Knowledge	100	2 months

## **Source Materials**

Primary source of readings:

 H. Daume III, A Course in Machine Learning v0.9. <u>http://ciml.info</u> (Good intro, focuses on machine learning concepts before math. Free online. Not finished.)

**Excellent supplements:** 

- K. Murphy, *Machine Learning: A Probabilistic Perspective*, MIT Press, 2012. (Great reference and in-depth coverage.)
- T. Mitchell, *Machine Learning,* McGraw-Hill, 1997. (Great intro, but old and expensive.)
- Ian Goodfellow and Yoshua Bengio and Aaron Courville, Deep Learning, MIT Press, 2016. (Good source for deep learning, free online: <u>https://www.deeplearningbook.org/</u>)
- C. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006
- R. Duda, P. Hart & D. Stork, *Pattern Classification* (2<sup>nd</sup> ed.), Wiley, 2000
- D. Barber, *Bayesian Reasoning and Machine Learning*, Cambridge University Press, 2012. (Free online!)
- T. Hastie, R. Tibshirani, J. Friedman, *The Elements of Statistical Learning*, Springer, 2009. (Free online!)



## Why Study Machine Learning: A Few Quotes

"A breakthrough in machine learning would be worth ten Microsofts."

-Bill Gates, Microsoft

"Machine learning is the next Internet." -Tony Tether, Former Director, DARPA

"Machine learning is the hot new thing." -John Hennessy, President, Stanford

"Web rankings today are mostly a matter of machine learning." -Prabhakar Raghavan, Dir. Research, Yahoo

"Machine learning is going to result in a real revolution." -Greg Papadopoulos, CTO, Sun



# **So What Is Machine Learning?**

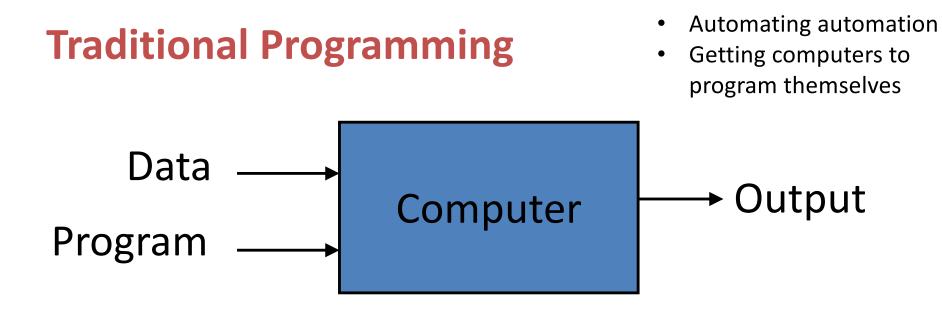
- Learning is acquiring and improving performance through experience.
- H. Simon: Any process by which a system improves its performance
- M. Minsky: Learning is making useful changes in our minds
- R. Michalsky: Learning is constructing or modifying representations of what is being experienced
- L. Viliant: Learning is the process of knowledge acquisition in the absence of explicit programming



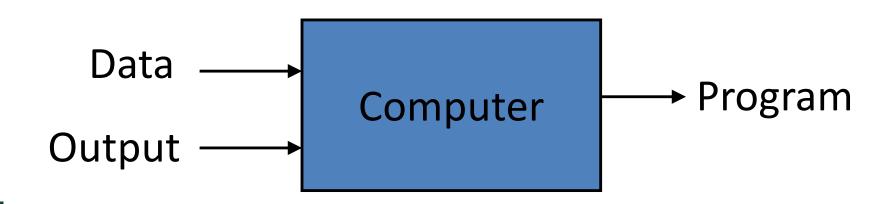
# **So What Is Machine Learning?**

- What does it mean for a computer to learn? Why would we want them to learn? How do we get them to learn?
- We want computers to learn when it is too difficult or too expensive to program them directly to perform a task → Automating automation
- Get the computer to program itself by showing examples of inputs and outputs.
- In reality: we will write a "parameterized" program, and let the learning algorithm find the set of parameters that best approximates the desired function or behavior → Let the data do the work!





## **Machine Learning**





## **Another view on machine learning**

- Machine learning = automated science (sort of)
- Goal is to go from raw data to useful knowledge
- An ML algorithm finds a theory to fit the data and background knowledge as well as possible.
- A theory is good if it has good predictive accuracy.



## **Related Fields**

- Fields that use machine learning:
  - Artificial intelligence
  - Computer vision: object detection, tracking, segmentation, ...
  - Natural language processing: machine translation, question answering, text generation, ...
  - Computational biology: sequence alignment, information extraction, ...
  - Robotics: state estimation, self-driving, ...
  - Medicine: medical diagnosis, treatment prediction, drug design, ...
  - Financial Analysis: portfolio allocation, option pricing (many people on Wall Street use machine learning)



## **Related Fields**

- Fields with similar goals to machine learning:
  - Statistical Estimation
  - Data mining
  - Data science
  - Psychology (developmental, cognitive)
- Fields used by machine learning:
  - Information theory
  - Numerical optimization
  - Computational complexity



## **Definition: Machine Learning!**

- T. Mitchell: Improving performance via experience
  - A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T as measured by P, improves with experience.



## Example 1: A Chess learning problem

- Task T: playing chess
- Performance measure P: percent of games won against opponents
- Training Experience E: playing practice games against itself



## Example 2: Autonomous Vehicle Problem

- Task T: driving on a public highway/roads using vision sensors
- Performance Measure P: percentage of time the vehicle is involved in an accident
- Training Experience E: a sequence of images and steering commands recorded while observing a human driver

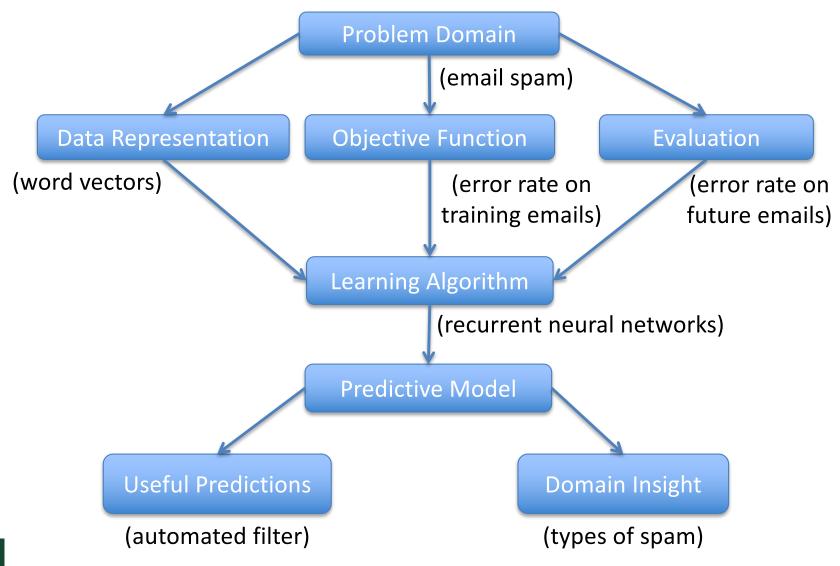


## Example 3: Machine Translation

- Task T: translating sentences from one language to another language
- Performance Measure P: the similarities between the machine-translated sentences and the human-translated sentences (BLUE scores)
- Training Experience E: pairs of translated sentences between languages provided by human



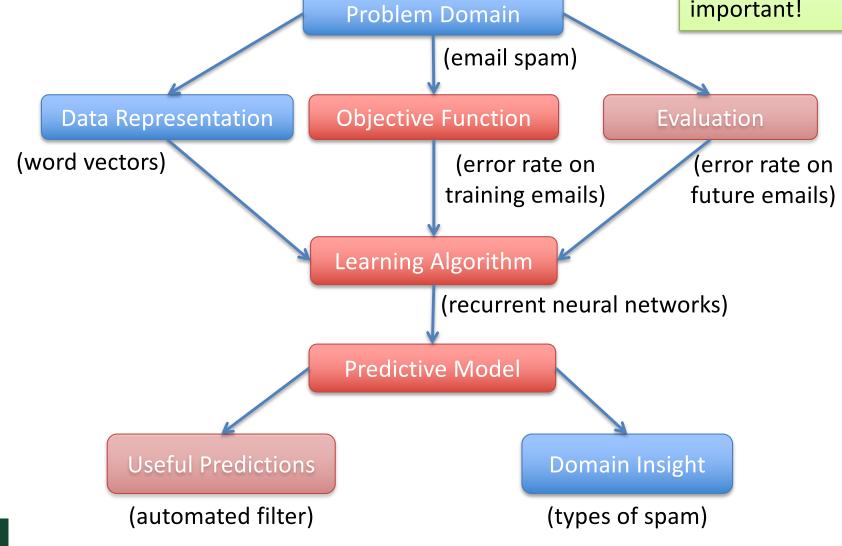
## The Big Picture







This class mostly focuses on the red pieces, but the blue pieces are just as important!





# ML in a Nutshell

- Tens of thousands of machine learning algorithms
- Hundreds new every year
- Some algorithms are specific to application domains/data
- Every machine learning algorithm has three components:
  - Model Representation
  - Evaluation
  - Optimization



## **Model Representation**

- Decision trees
- Instance-based models
- Linear function (hyperplane)
- Support vector machines
- Kernel methods
- Neural networks/Deep learning (Transformers)
- (Model ensembles)
- (Sets of rules / Logic programs)
- (Graphical models (Bayes/Markov nets))
- Etc.



## **Evaluation**

- Accuracy
- Precision and recall
- Squared error
- Likelihood
- Posterior probability
- Cost / Utility
- Margin
- Entropy
- KL divergence
- Etc.



# Optimization

- Combinatorial optimization
  - E.g.: Greedy search
- Convex optimization
  - E.g.: Gradient descent
- Constrained optimization
  - E.g.: Linear programming



# **Types of Learning**

#### • Based on the information available

- Supervised (inductive) learning
  - Training data includes desired outputs
- Unsupervised learning
  - Training data does not include desired outputs
  - Find hidden structure in data
- Semi-supervised learning
  - Training data includes a few desired outputs
- Reinforcement learning
  - The learner interacts with the world via "actions" and tries to find an optimal policy of behavior with respect to "rewards" it receives from the environment
- Based on the role of the learner
  - Passive Learning
    - Training solely relies on data
  - Active Learning
    - Training additionally involves interactions with human



## Types of Supervised Learning Problems

- Classification: predict a discrete/categorical value from a predefined set of values
- **Regression:** predict a continuous/real value
- Structured prediction: predict a complex output, such as a sequence or tree



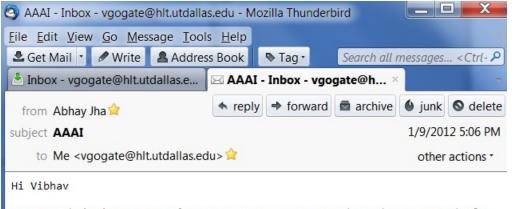
# Machine Learning: Applications

# Examples of what you will study in class in action!



## **Classification Example: Spam Filtering**

ile <u>E</u> dit <u>V</u> iew <u>G</u> o <u>M</u> essage <u>T</u> ools <u>H</u> elp ✿ Get Mail ·	े Search all messages <ctrl- th="" २<=""></ctrl->				
📕 Trash - vgogate@gmail.com 🖂 Online Casino - \$3000 Bon ×					
▲ reply ≪ reply all + forward	🖻 archive 🕚 junk 🛇 delete				
from Nellie Correa <mary.collins@mail2southdakota.com>☆</mary.collins@mail2southdakota.com>					
subject Online Casino - \$3000 Bonus at Casino Titan 12/22/2009 2:10 AM					
to vgogate@ics.uci.edu	other actions •				
Blackjack, Slot Machines, Roulette, Craps, Keno and many simply <u>download Casino Titan free online gambling softwa</u> you can be on your way to cashing in on the best casino or	re, and in a few simple steps				



Are we submitting to AAAI ? In any case, can you send me the current draft. I have a camera ready deadline tomorrow; we can skype sometime on Wed if you are free.

Abhay

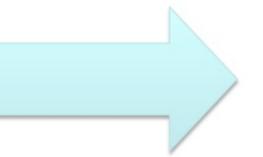
## Classify as "Spam" or "Not Spam"



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## Classification Example: Weather Prediction











## Regression example: Predicting Gold/Stock prices



Good ML can make you rich (but there is still some risk involved).

# Given historical data on gold prices, predict tomorrow's price!



## **Similarity Determination**



1. Search mode: Theme 2. Find similar by Color / Texture



1. Find similar by Theme ..... OR ..... 2. Find similar by Color / Texture



..... OR ..... 2. Find similar by Color / Texture



----- OR -----



1. Find similar by Theme ..... OR ..... 2. Find similar by Color / Texture



----- OR ------2. Find similar by Color / Texture



----- OR ------



1. Find similar by Theme ..... OR ..... 2. Find similar by Color / Texture



---- OR -----2. Find similar by Color / Texture



1. Find similar by Theme 2. Search mode: Color / Texture



..... OR .....



---- OR --





..... OR .....

THIS PHOTO IS CURRENTLY UNAVAILABLE.

1. Find similar by Theme

OR ..... 2. Find similar by Color / Texture

flickr

.... OR .....



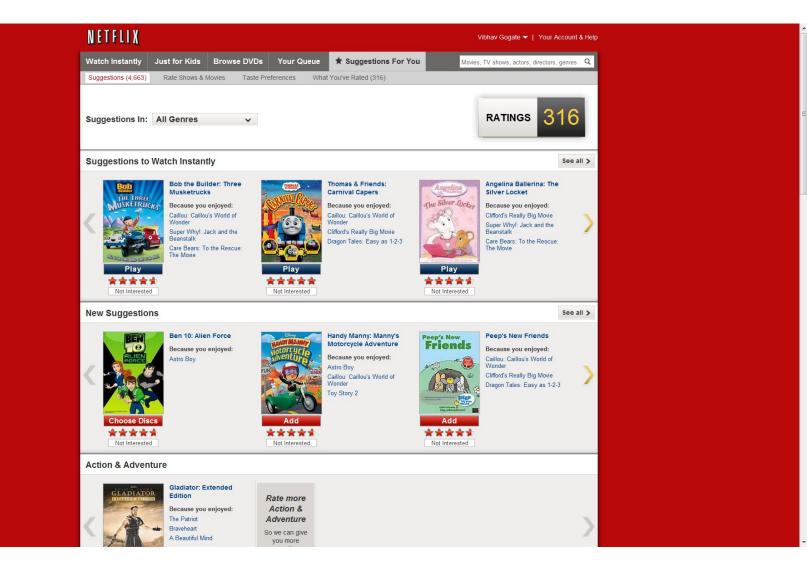






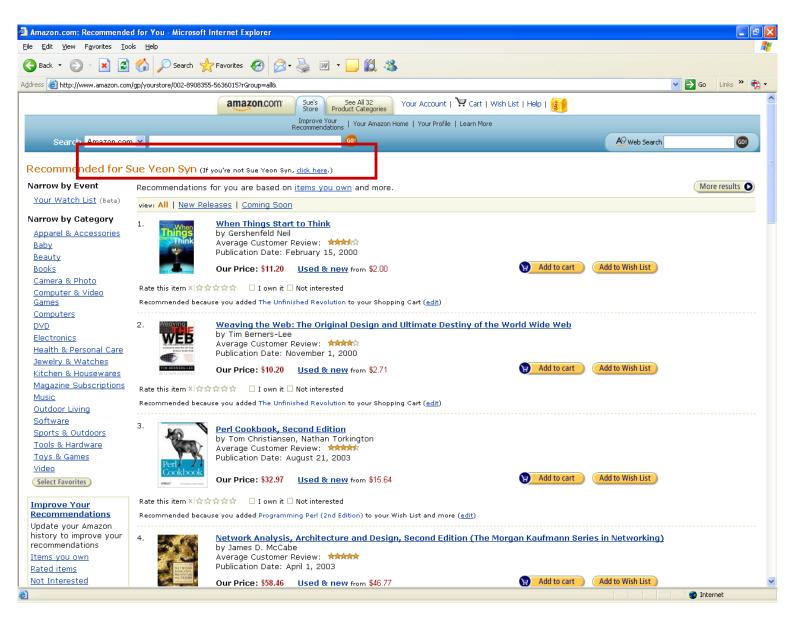


## **Collaborative Filtering**



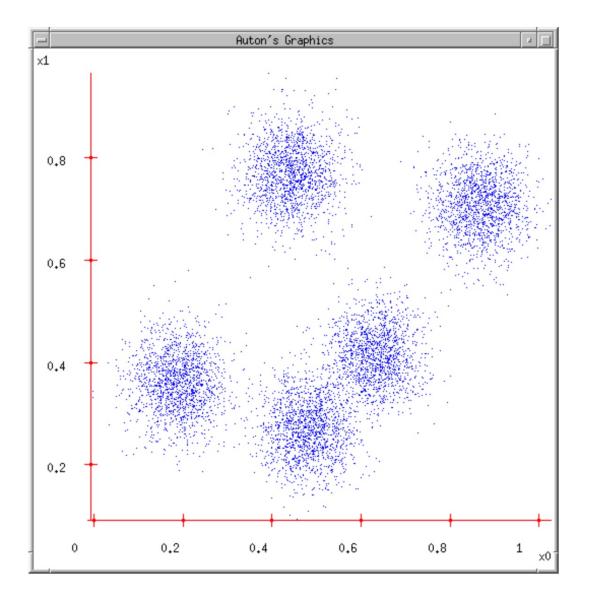


## **Collaborative Filtering**

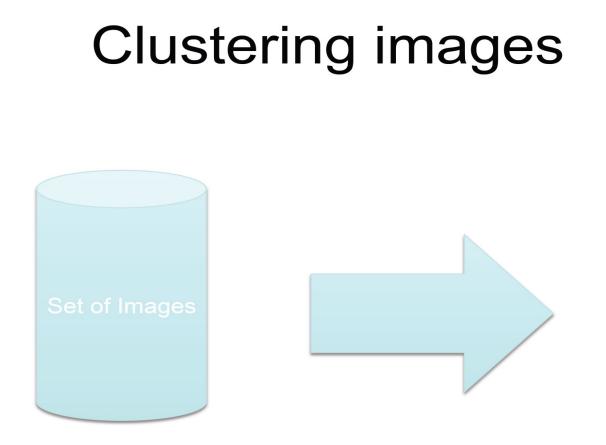




## **Clustering: Discover Structure in data**





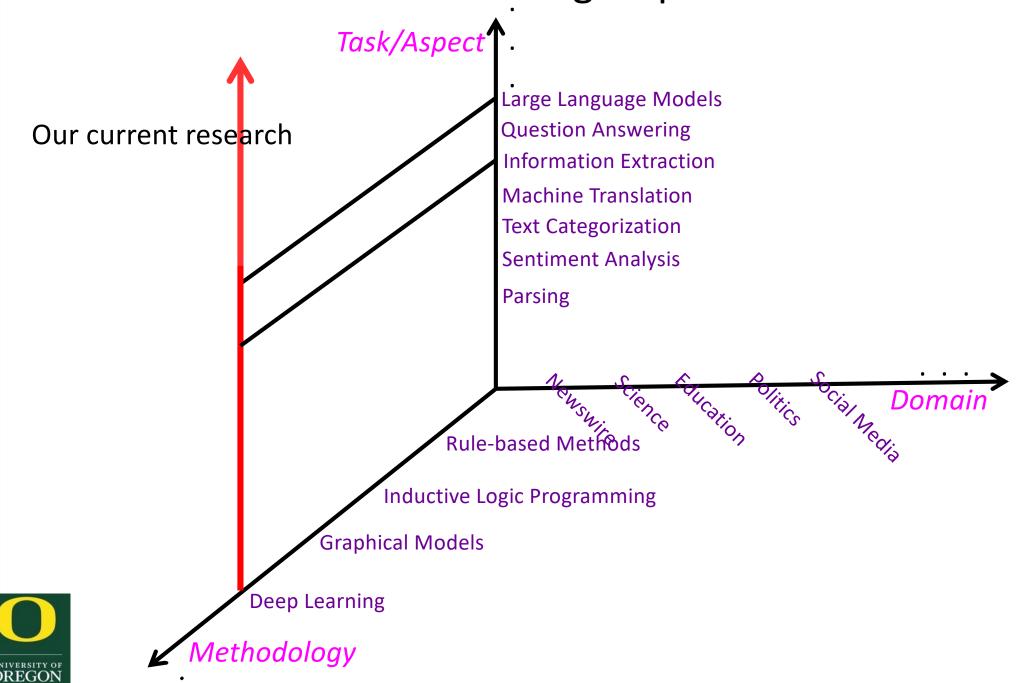




[Goldberger et al.]



### Research in the NLP group at UO



## Information extraction



Giuliani, 58, proposed to Nathan, a former nurse, during a business trip to Paris \_\_\_\_\_ five months after he finalized his divorce from Donna Hanover in July after 20 years of marriage.



#### Relation **Knowledge Base**

Name	leaderOf	
Giuliani	New York City	

Corpora

**Entity Recognition** 

**Trigger Prediction** 

**Relation Extraction** 

**Argument Prediction** 

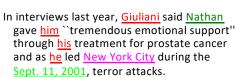
**Coreference Resolution** 

**Entity Linking** 

Event Knowledge Base

Trigger	Туре	Person1	Person 2	Time
divorce	Divorce	Giuliani	Donna Hanover	July







#### CS 472/572: Machine Learning

## Neural Networks for Relation Extraction SemEval 2010 Dataset

Classifier

MaxEnt

SVM

CNN

2014)

CNN

2015a)

(Zeng et al.,

(Nguyen and Grishman,

Features

WordNet

POS, WordNet, morphological

features, noun compound sys-

POS, WordNet, prefixes and

other morphological fea- tures, dependency parse, Levin classes, PropBank, FrameNet, NomLex-Plus, Google n -grams,

paraphrases, TextRunner

tem, thesauri, Google n -grams

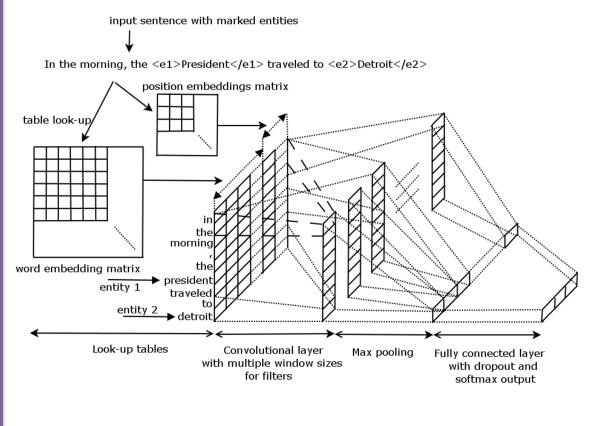
F

77.6

82.2

82.7

82.8



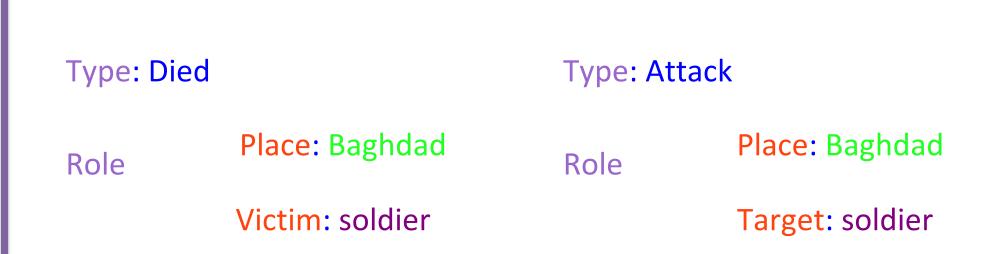
A Convolutional Neural Network (CNN) for Relation Extraction



#### Nguyen and Grishman, 2015a

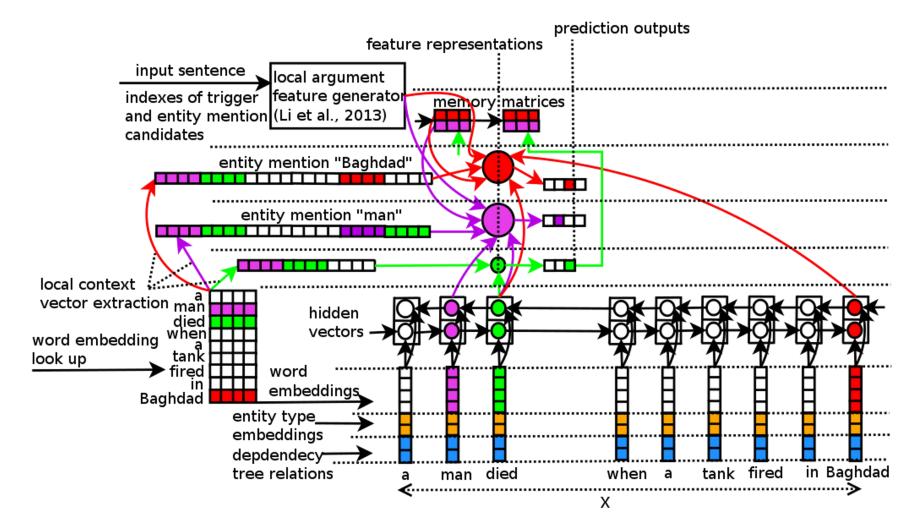
# **Event Extraction**

In Baghdad, a soldier *died* when his tank *fired* on the street.



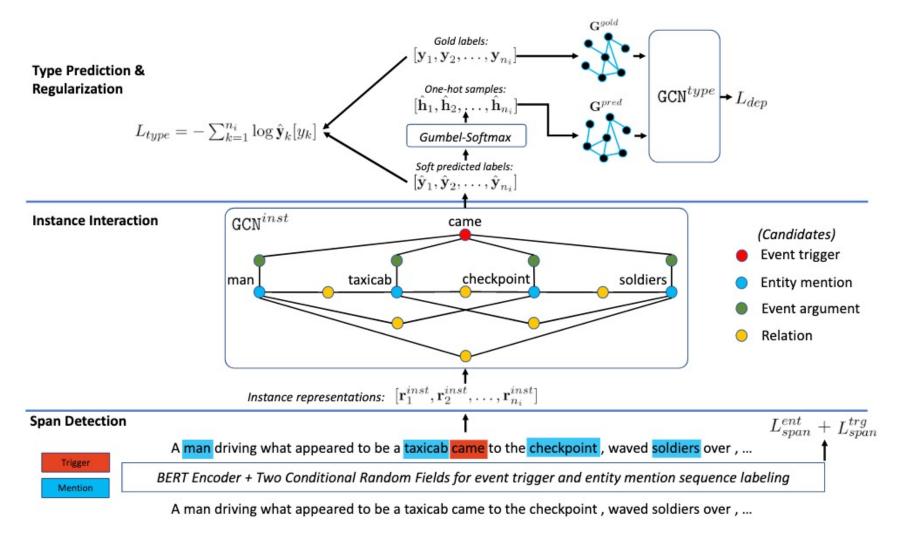


## Joint Inference for Event Extraction





## Joint Inference for Event Extraction





### Nguyen et al., 2021 (NAACL 2021)

Demo: <u>http://nlp.uoregon.edu/fourie</u>

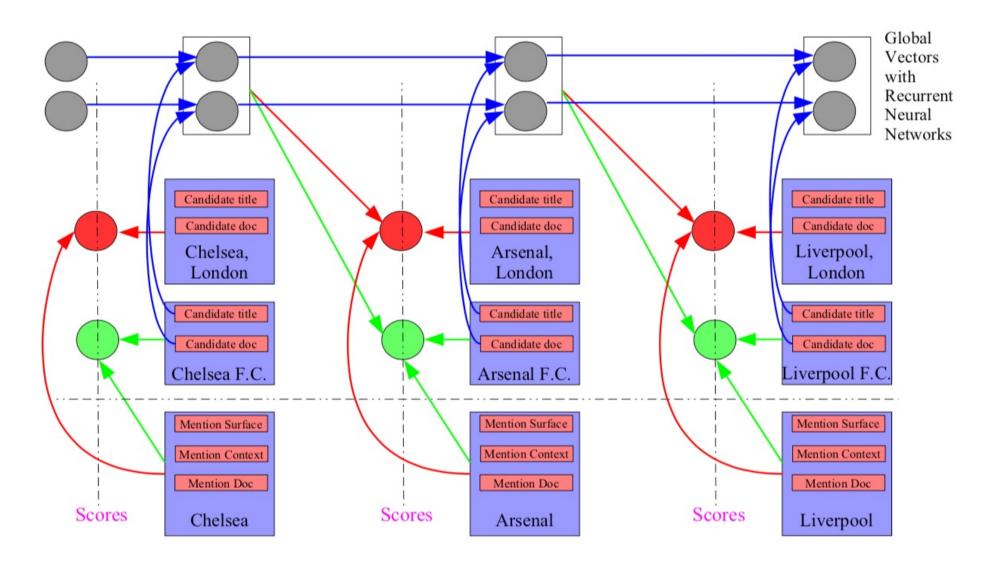
# **Entity Linking**



<u>Chelsea</u> have long-standing rivalries with <u>North London</u> clubs <u>Arsenal</u> and <u>Tottenham</u> <u>Hotspur</u>. A strong rivalry with <u>Leeds United</u> dates back to several heated and controversial matches in the 1960s and 1970s.



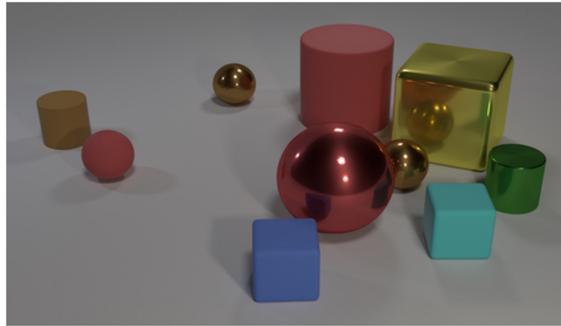
## Joint Inference for Entity Linking





Nguyen et al., 2016 (COLING 2016)

# Visual Question Answering (VQA)



Q: Are there an equal number of large things and metal spheres? Q: What size is the cylinder that is left of the brown metal thing that is left of the big sphere?

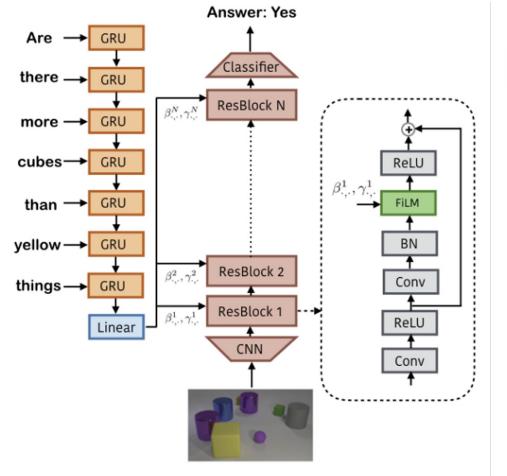
Q: There is a **sphere** with the **same size as** the **metal cube**; is it **made of the same material as** the **small red sphere**?

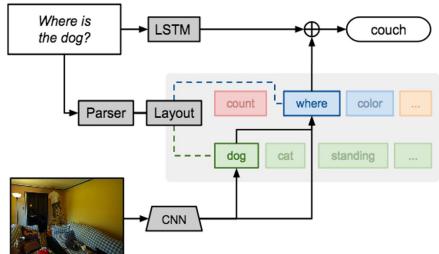
Q: How many objects are either small cylinders or red things?



Johnson et al., 2017

# **VQA** Models





Neural Module Networks Jacob et al., 2017



## FiLM: Ethan et al., 2018

# ChatGPT



if A ~ Normal(1, 2) and B ~ Normal(2, 3), and A and B are independent, what is the expected value of A + B



The expected value of the sum of two random variables is equal to the sum of their individual expected values. Therefore, we can find the expected value of A + B by adding the expected values of A and B:

E(A + B) = E(A) + E(B)

Since A ~ Normal(1, 2), we know that the expected value of A is 1, and since B ~ Normal(2, 3), we know that the expected value of B is 2. Therefore:

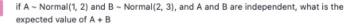
E(A + B) = E(A) + E(B) = 1 + 2 = 3

So the expected value of A + B is 3.



### CS 472/572: Machine Learning

# ChatGPT



The expected value of the sum of two random variables is equal to the sum of their individual expected values. Therefore, we can find the expected value of A + B by adding the expected values of A and B:

E(A + B) = E(A) + E(B)

Since A  $\sim$  Normal(1, 2), we know that the expected value of A is 1, and since B  $\sim$  Normal(2, 3), we know that the expected value of B is 2. Therefore:

E(A + B) = E(A) + E(B) = 1 + 2 = 3

So the expected value of A + B is 3.

What if A and B are not independent?

If A and B are not independent, then we cannot simply add their expected values to defined their expected value of their sum.

To find the expected value of A + B when A and B are not independent, we need to know the joint distribution of A and B or the covariance between A and B. If we have the joint distribution, we can use the following formula:

E(A + B) = E(A) + E(B) + Cov(A, B)

where Cov(A, B) is the covariance between A and B.

If we do not have the joint distribution of A and B, but we know their covariance, then we can use the following formula:

E(A + B) = E(A) + E(B) + Cov(A, B)

 $= E(A) + E(B) + \rho(A,B)\sigma(A)\sigma(B)$ 

where  $\rho(A,B)$  is the correlation coefficient between A and B, and  $\sigma(A)$  and  $\sigma(B)$  are the standard deviations of A and B, respectively.

In summary, if A and B are not independent, we need to consider their joint distribution or their covariance to calculate the expected value of A + B.

You

If A ~ Normal(1, 2) and B ~ Normal(2, 3), and A and B are independent. What is the expected value of A + B?

#### ChatGPT

If A and B are independent random variables, then the expected value of their sum is simply the sum of their individual expected values.

Given that A ~ Normal(1, 2) and B ~ Normal(2, 3), we have:

- E(A) = 1 (the mean of A)
- E(B) = 2 (the mean of B)

So, the expected value of A + B is:

E(A + B) = E(A) + E(B) = 1 + 2 = 3.

You What if A and B are not independent?

#### ChatGPT

If A and B are not independent, we need more information about their joint distribution or the covariance between them to determine the expected value of their sum.

Without knowledge of their joint distribution or covariance, we cannot simply add their individual expected values to find the expected value of their sum. In cases where A and B are not independent, the expected value of their sum depends on the specific relationship between them, which requires further information beyond their marginal distributions.



## Text-to-Video

## • Sora (OpenAI)

A beautiful homemade video showing the people of Lagos, Nigeria in the year 2056. Shot with a mobile phone camera.

A drone camera circles around a beautiful historic church built on a rocky outcropping along the Amalfi Coast, the view showcases historic and magnificent architectural details and tiered pathways and patios, waves are seen crashing against the rocks below as the view overlooks the horizon of the coastal waters and hilly landscapes of the Amalfi Coast Italy, several distant people are seen walking and enjoying vistas on patios of the dramatic ocean views, the warm glow of the afternoon sun creates a magical and romantic feeling to the scene, the view is stunning captured with beautiful photography.











A gorgeously rendered papercraft world of a coral reef, rife with colorful fish and sea creatures

# Machine learning has grown in leaps and bounds

- The main approach for
  - Speech Recognition
  - Robotics
  - Natural Language Processing
  - Computational Biology
  - Sensor networks
  - Computer Vision
  - Web
  - ...and many more each year...



# What We'll Cover

- Supervised learning: Decision tree induction, Instance-based learning, Neural networks/Deep Learning, Support vector machines, Linear regression, Learning theory, Transformers, etc.
- General machine learning concepts and techniques: Feature selection, cross-validation, algorithm evaluation ...
- **Unsupervised learning:** Clustering, Dimensionality reduction, Auto-Encoder, VAE, GAN, Diffusion (if time permitted)

## Not covering:

- Reinforcement learning
- Probabilistic graphical models (410/510)
- Structured prediction (e.g., machine translation, image segmentation, multi-label classification)



# What We'll Cover: Comparison

## **Computer Science**

- Core concepts: Variables, conditionals, loops, functions, etc.
- Key algorithms: Mergesort, linked lists, binary search trees, breadth-first search, etc.
- Process:

Debugging, software engineering, etc.

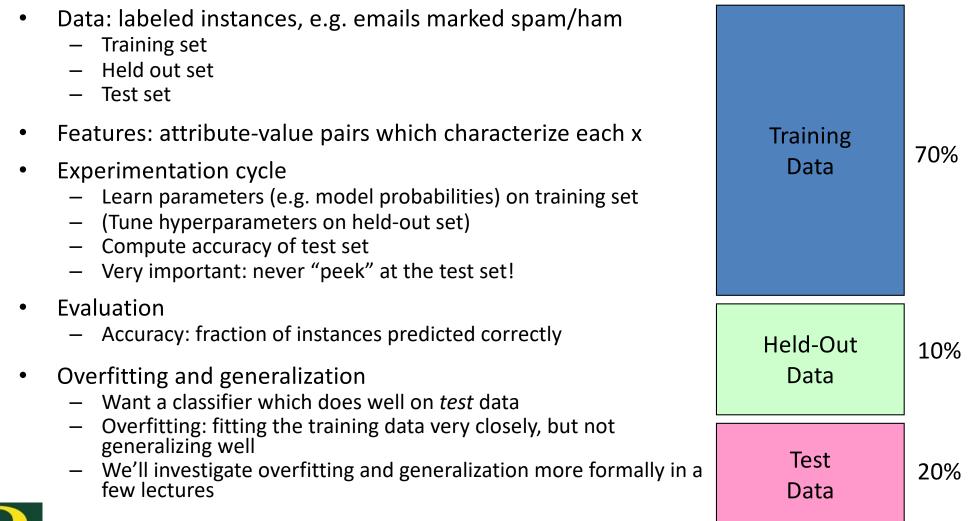
## **Machine Learning**

- Core concepts: Classification, overfitting, underfitting, training set, etc.
- Key algorithms: Decision trees, nearest neighbor, linear models, etc.
- Process:

Designing and debugging ML systems



# Important Concepts





CS 472/572: Machine Learning		I				
	Rating	Easy?	AI?	Sys?	Thy?	Morning?
	+2	У	У	n	У	n
Goal: Use course	+2	У	У	n	У	n
attributes to predict the student's course rating	+2	n	У	n	n	n
	+2	n	n	n	У	n
	+2	n	У	У	n	У
	+1	У	У	n	n	n
(+2 = loved it, -2 =	+1	У	У	n	У	n
hated it).	+1	n	У	n	У	n
How should we model this?	0	n	n	n	n	У
	0	У	n	n	У	У
	0	n	У	n	У	n
	0	У	У	У	У	У
	-1	У	У	У	n	У
	-1	n	n	У	У	n
	-1	n	n	У	n	У
	-1	У	n	У	n	У
	-2	n	n	У	У	n
	-2	n	У	У	n	У
	-2	У	n	У	n	n
	-2	у	n	У	n	У
(Data is from CIML appendix	ndix.)					

**OREGON** (Data is from CIML appendix.)

# The Big Picture

