Announcements

Assignments:

- HW6
  - Due Tue 3/5, 10 pm
- P3
  - Due Thu 3/7, 10 pm

Spring Break!

- No recitation this Friday
- HW7 (online): out Wed 3/6, due Tue 3/19
- P4: out after break, due Thu 3/28
AI: Representation and Problem Solving

Knowledge Representation

Instructors: Pat Virtue & Stephanie Rosenthal

Slide credits: CMU AI, especially Tom Mitchell (NELL)
What is this?
What is this?
Ontologies

WordNet/ImageNet

https://wordnet.princeton.edu/
http://www.image-net.org/
Ontologies

ImageNet

https://wordnet.princeton.edu/
http://www.image-net.org/
An “upper ontology” of the world

AIMA, Figure 12.1
Taxonomic Hierarchies

10 million living and extinct species.
THE DECISION MAKERS TAXONOMY
VIDEO GAME MOOD TAXONOMY

INTRODUCTION
The mood taxonomy, developed by the Game Metadata Research Group, in collaboration with the SIMM, is part of the Video Game Metadata Schema. This project expands upon current research, furthering our understanding of how people perceive and describe the mood of video games and interactive media.

METHOD
Metadata video game title list with 1500+ titles.
User Study and Exercise: 20 gamers completed questionnaires, were interviewed and asked to apply mood terms to popular video game titles.

RESULTS
Study Data: interview transcripts and exercise data.
Data Analysis: sample of 300 games with sourced game and year (from allgame.com).
Term Suggestions: mood term suggestions collected from gameDNA and interview data.
Mood Clustering: hierarchical clustering of current preferred terms.

MOOD STUDY DATA ANALYSIS
As part of the exercise, participants were asked to apply mood terms to 35 video game titles. Below are the four most recognized video game titles with their applied mood terms.

ANGRY BIRDS
- light-hearted
- humorous
- fast-paced
- competitive

ASSASSIN'S CREED III
- dramatic
- intense
- historical
- mysterious

GRAND THEFT AUTO IV
- exciting
- fast-paced
- realistic
- atmospheric

SUPER MARIO BROS.
- light-hearted
- playful
- cute
- adventurous

While a large number of participants applied the same top mood term to Angry Birds (light-hearted), Assassin's Creed III (dramatic) and Grand Theft Auto IV (exciting). opinion was more split over Super Mario Bros.

MOOD CLUSTER DATA

This graph represents mood terms that appear frequently together in the collected interview data. The results indicate that the mood terms intense and aggressive, light-hearted and cute, and horror and dark are applied often together when describing video game mood. Clustering mood terms will allow us to use groups of particular mood terms instead of individual terms to obtain more consistent results.

MOOD TERM SUGGESTIONS

Preferred Terms
- light-hearted
- humorous
- fast-paced
- competitive

Equivalent Terms
- amusing
- funny
- lively
- spirited

MOOD TERM BY GENRE

The diagram to the left explores the genre breakdown of mood terms applied to a sample of 300 games. The top three mood terms are represented by dark blue, orange, and light blue lines, respectively.
Categories and Objects

First-order logic for ontological representations

Category: Basketball

- Predicate: \( \text{Basketball}(b) \)
- Object for category: \( \text{Basketballs} \)
  - \( \text{Member}(b, \text{Basketballs}) \)
    - Notation shortcut: \( b \in \text{Basketballs} \)
  - \( \text{Subset}(\text{Basketballs}, \text{Balls}) \)
    - Notation shortcut: \( \text{Basketball} \subseteq \text{Balls} \)
- Specific object
  - \( \text{Basketball}_{12} \in \text{Basketballs} \)

Reification: converting category predicate into an object
Categories and Objects

Decompositions and Partitions

$\text{Disjoint}\left(\{\text{Animals, Vegetables}\}\right)$

$\text{ExhaustiveDecomposition}\left(\{\text{Canadians, Americans, Mexicans}, \text{ NorthAmericans}\}\right)$

$\text{Partition}\left(\{\text{Canada, United States, Mexico}, \text{ NorthAmericanCountries}\}\right)$
Categories and Objects

Parts

\( PartOf(\text{Bucharest, Romania}) \)
\( PartOf(\text{Romania, EasternEurope}) \)
\( PartOf(\text{EasternEurope, Europe}) \)

Transitive

\( PartOf(x, y) \land PartOf(y, z) \Rightarrow PartOf(x, z) \)

Reflexive

\( PartOf(x, x) \)
Categories and Objects

Measurements

Number are objects

Units are typically functions to convert number constants to measurements

\[ \text{Length}(L_1) = \text{Inches}(1.5) = \text{Centimeters}(3.81) \]
Which of these measurement statements makes sense? Select ALL that apply.

A) Diameter(Basketball)
B) Diameter(Basketball_{12})
C) Weight(Apple)
D) Weight(Apple_{1} \land Apple_{2} \land Apple_{3})
E) None of the above
Piazza Poll 1

Which of these measurement statements makes sense?
Select ALL that apply.

A) \(\text{Diameter}(\text{Basketball})\)  
   Maybe, if we have default diameter the Basketball category

B) \(\text{Diameter}(\text{Basketball}_{12})\)  
   Yes

C) \(\text{Weight}(\text{Apple})\)  
   Probably not. Not all apples in the category Apple have the same weight

D) \(\text{Weight}(\text{Apple}_1 \land \text{Apple}_2 \land \text{Apple}_3)\)  
   No. This is invalid, as the arg to Weight is a sentence not a term, e.g. \(\text{Weight}(\text{True})\) doesn't make sense

E) None of the above
Categories and Objects

Bunches of Things and Stuff

\[ \text{BunchOf}\left(\{\text{Apple}_1, \text{Apple}_2, \text{Apple}_3\}\right) \]

Things

- Countable
- “The” apple, “an” apple

Stuff

- More of a mass
- “Some” water

\[ b \in \text{Butter} \land \text{PartOf}\left(p, b\right) \Rightarrow p \in \text{Butter} \]
Events

How to handle fluents?

President(USA)
President(USA, t)

\[ T(Equals(President(USA), GeorgeWashington), AD1790) \]
Events

How to handle time?

AIMA, Figure 12.2
Semantic Networks

A graphical representation for some types of knowledge

- Once viewed as an “alternative” to logic (it’s not really)
- The IS-A relation often forms the backbone of a semantic network

Vertebrate
  ▲ IS-A
Mammal
  ▲ IS-A
Elephant
  ▲ InstanceOf
Clyde
Semantic Networks

Reasoning with default information

Dog
- Barks
- Has Fur
- Has four legs

Buster
- ✓
- ✓
- ✗
Semantic Networks

Reasoning with default information
Input, More Input!
Knowledge Representation in the Wild

- WordNet
- ImageNet
- Wikimedia: Wikipedia, WikiData
- Google Knowledge Graph
- Schema.org
- The “Semantic Web”
- NELL: Never Ending Language Learning
Knowledge panels in Google search results

The panels are generated from what’s called the **Google Knowledge Graph**.

Data comes from Wikipedia, CIA World Factbook, and other online sources.

As of Oct. 2016, held 70 billion facts.
import json
import urllib
api_key = open('.api_key').read()
query = 'Taylor Swift'
service_url = 'https://kgsearch.googleapis.com/v1/entities:search'
params = {
    'query': query,
    'limit': 10,
    'indent': True,
    'key': api_key,
}

url = service_url + '?' + urllib.urlencode(params)
response = json.loads(urllib.urlopen(url).read())
for element in response['itemListElement']:
    print element['result']['name'] + ' (' + str(element['resultScore']) + ')'
Taylor Swift

Singer-songwriter

URL: https://en.wikipedia.org/wiki/Taylor_Swift
License: http://creativecommons.org/licenses/by-sa/2.0
“Person” schema at schema.org

Person
Canonical URL: http://schema.org/Person

Thing > Person
A person (alive, dead, undead, or fictional).

Usage: Over 1,000,000 domains
The Semantic Web

- Term coined by Tim Berners-Lee
- Common framework for exchange of data across application, enterprise, and community boundaries
- HTML defines how text should look when presented to humans
- Semantic web markup defines how information should be organized to be interpretable by machines
- “Ontology engineer” is a job description now
NELL: Never-Ending Language Learner

Inputs:
• initial ontology
• few examples of each ontology predicate
• the web
• occasional interaction with human trainers

The task:
• run 24x7, forever
• each day:
  1. extract more facts from the web to populate the initial ontology
  2. learn to read (perform #1) better than yesterday
NELL Overview

Running 24x7, since January, 12, 2010

Inputs:
- ontology defining >600 categories and relations
- 10-20 seed examples of each
- 500 million web pages
- 100,000 web search queries per day
- ~ 5 minutes/day of human guidance

Result:
- KB with > 15 million candidate beliefs, growing daily
- learning to reason, as well as read
- automatically extending its ontology
NELL Website

- http://rtw.ml.cmu.edu ← follow NELL here

Recently-Learned Facts

<table>
<thead>
<tr>
<th>instance</th>
<th>iteration</th>
<th>date learned</th>
<th>confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>shamattawa_river is a river</td>
<td>1111</td>
<td>06-jul-2018</td>
<td>100.0</td>
</tr>
<tr>
<td>capitol_theatre_oh is a stadium or event venue</td>
<td>1111</td>
<td>06-jul-2018</td>
<td>100.0</td>
</tr>
<tr>
<td>japanese_judge is a judge</td>
<td>1111</td>
<td>06-jul-2018</td>
<td>98.4</td>
</tr>
<tr>
<td>saturday_meetings is a TV show</td>
<td>1111</td>
<td>06-jul-2018</td>
<td>100.0</td>
</tr>
<tr>
<td>trolley_museum is a museum</td>
<td>1111</td>
<td>06-jul-2018</td>
<td>100.0</td>
</tr>
<tr>
<td>subaru makes the automobile legacy</td>
<td>1114</td>
<td>25-aug-2018</td>
<td>98.4</td>
</tr>
<tr>
<td>jacksonville_jaguars is a sports team also known as steelers</td>
<td>1112</td>
<td>24-jul-2018</td>
<td>98.4</td>
</tr>
<tr>
<td>steve001 is an athlete who injured his/her knee</td>
<td>1112</td>
<td>24-jul-2018</td>
<td>99.6</td>
</tr>
<tr>
<td>dodge is a specific automobile maker dealer in ohio</td>
<td>1115</td>
<td>03-sep-2018</td>
<td>96.9</td>
</tr>
<tr>
<td>cristhian_martinez plays the sport baseball</td>
<td>1116</td>
<td>12-sep-2018</td>
<td>96.9</td>
</tr>
</tbody>
</table>
Default Approach

Extract cities:

- Paris
- Pittsburgh
- Seattle
- Cupertino

San Francisco
Austin
denial

anxiety
selfishness
Berlin

mayor of arg1
live in arg1

arg1 is home of
traits such as arg1

Its underconstrained!!
Key Idea 1: Coupled semi-supervised training of many functions

hard (underconstrained) semi-supervised learning problem

much easier (more constrained) semi-supervised learning problem
Type 1 Coupling: Co-Training, Multi-View Learning

[Blum & Mitchell; 98]
[Dasgupta et al; 01]
[Ganchev et al., 08]
[Sridharan & Kakade, 08]
[Wang & Zhou, ICML10]
Type 2 Coupling: Multi-task, Structured Outputs

[Daume, 2008]
[Bakhir et al., eds. 2007]
[Roth et al., 2008]
[Taskar et al., 2009]
[Carlson et al., 2009]

NP

athlete(NP) → person(NP)
athlete(NP) → NOT sport(NP)
NOT athlete(NP) ← sport(NP)
Multi-view, Multi-Task Coupling

NP:
- NP text context distribution
- NP morphology
- NP HTML contexts
Learning Relations between NP’s

np1

playsForTeam(a,t)

playsSport(a,s)

teamPlaysSport(t,s)

coachesTeam(c,t)

np2
Type 3 Coupling: Argument Types

playsSport(NP1,NP2) → athlete(NP1), sport(NP2)

Over 2500 coupled functions in NELL
Basic NELL Architecture

Knowledge Base (latent variables)
- Beliefs
- Candidate Beliefs

Evidence Integrator

Continually Learning Extractors

Text Context patterns (CPL)
HTML-URL context patterns (SEAL)
Morphology classifier (CML)
NELL: Learned reading strategies

Plays_Sport(arg1,arg2):
  \( \text{arg1} \text{ was playing } \text{arg2} \) \( \text{arg2} \text{ megastar } \text{arg1} \) \( \text{arg2} \text{ icons } \text{arg1} \)
  \( \text{arg2} \text{ player named } \text{arg1} \) \( \text{arg2} \text{ prodigy } \text{arg1} \)
  \( \text{arg1} \text{ is the tiger woods of } \text{arg2} \) \( \text{arg2} \text{ career of } \text{arg1} \)
  \( \text{arg2} \text{ greats as } \text{arg1} \) \( \text{arg1} \text{ plays } \text{arg2} \) \( \text{arg2} \text{ player is } \text{arg1} \)
  \( \text{arg2} \text{ legends } \text{arg1} \) \( \text{arg1} \text{ announced his retirement from } \text{arg2} \)
  \( \text{arg2} \text{ operations chief } \text{arg1} \) \( \text{arg2} \text{ player like } \text{arg1} \)
  \( \text{arg2} \text{ and golfing personalities including } \text{arg1} \) \( \text{arg2} \text{ players like } \text{arg1} \)
  \( \text{arg2} \text{ greats like } \text{arg1} \) \( \text{arg2} \text{ players are steffi graf and } \text{arg1} \)
  \( \text{arg2} \text{ great } \text{arg1} \) \( \text{arg2} \text{ champ } \text{arg1} \) \( \text{arg2} \text{ greats such as } \text{arg1} \)
  \( \text{arg2} \text{ professionals such as } \text{arg1} \) \( \text{arg2} \text{ hit by } \text{arg1} \) \( \text{arg2} \text{ greats } \text{arg1} \)
  \( \text{arg2} \text{ icon } \text{arg1} \) \( \text{arg2} \text{ stars like } \text{arg1} \) \( \text{arg2} \text{ pros like } \text{arg1} \)
  \( \text{arg1} \text{ retires from } \text{arg2} \) \( \text{arg2} \text{ phenom } \text{arg1} \) \( \text{arg2} \text{ lesson from } \text{arg1} \)
  \( \text{arg2} \text{ architects robert trent jones and } \text{arg1} \) \( \text{arg2} \text{ sensation } \text{arg1} \)
  \( \text{arg2} \text{ pros } \text{arg1} \) \( \text{arg2} \text{ stars venus and } \text{arg1} \) \( \text{arg2} \text{ hall of famer } \text{arg1} \)
  \( \text{arg2} \text{ superstar } \text{arg1} \) \( \text{arg2} \text{ legend } \text{arg1} \) \( \text{arg2} \text{ legends such as } \text{arg1} \)
  \( \text{arg2} \text{ players is } \text{arg1} \) \( \text{arg2} \text{ pro } \text{arg1} \) \( \text{arg2} \text{ player was } \text{arg1} \)
  \( \text{arg2} \text{ god } \text{arg1} \) \( \text{arg2} \text{ idol } \text{arg1} \) \( \text{arg1} \text{ was born to play } \text{arg2} \)
  \( \text{arg2} \text{ star } \text{arg1} \) \( \text{arg2} \text{ hero } \text{arg1} \) \( \text{arg2} \text{ players are } \text{arg1} \)
  \( \text{arg1} \text{ retired from professional } \text{arg2} \) \( \text{arg2} \text{ legends as } \text{arg1} \)
  \( \text{arg2} \text{ autographed by } \text{arg1} \) \( \text{arg2} \text{ champion } \text{arg1} \) ...
If coupled learning is the key, how can we get new coupling constraints?
Key Idea 2:

Discover New Coupling Constraints

- first order, probabilistic horn clause constraints:

\[
0.93 \text{athletePlaysSport}(?x, ?y) \leftarrow \text{athletePlaysForTeam}(?x, ?z) \land \text{teamPlaysSport}(?z, ?y)
\]

- connects previously uncoupled relation predicates

- infers new beliefs for KB
Example Learned Horn Clauses

0.95 \( \text{athletePlaysSport}(?x, \text{basketball}) \leftarrow \text{athleteInLeague}(?x, \text{NBA}) \)

0.93 \( \text{athletePlaysSport}(?x, ?y) \leftarrow \text{athletePlaysForTeam}(?x, ?z) \)
\hspace{1em} \text{teamPlaysSport}(?z, ?y) \)

0.91 \( \text{teamPlaysInLeague}(?x, \text{NHL}) \leftarrow \text{teamWonTrophy}(?x, \text{Stanley_Cup}) \)

0.90 \( \text{athleteInLeague}(?x, ?y) \leftarrow \text{athletePlaysForTeam}(?x, ?z), \)
\hspace{1em} \text{teamPlaysInLeague}(?z, ?y) \)

0.88 \( \text{cityInState}(?x, ?y) \leftarrow \text{cityCapitalOfState}(?x, ?y), \text{cityInCountry}(?y, \text{USA}) \)

0.62* \( \text{newspaperInCity}(?x, \text{New_York}) \leftarrow \text{companyEconomicSector}(?x, \text{media}) \)
\hspace{1em} \text{generalizations}(?x, \text{blog}) \)
Some rejected learned rules

cityCapitalOfState{?x ?y} \leftarrow \text{cityLocatedInState}{?x ?y}, \text{teamPlaysInLeague}{?y \text{nba}}

teamplayssport{?x, \text{basketball}} \leftarrow \text{generalizations}{?x, \text{university}}
Learned Probabilistic Horn Clause Rules

0.93 \text{playsSport}(?x,?y) \leftarrow \text{playsForTeam(?x,?z), teamPlaysSport(?z,?y)}
Key Idea 3:
Automatically extend ontology
Ontology Extension (1) [Mohamed et al., EMNLP 2011]

Goal:
• Add new relations to ontology

Approach:
• For each pair of categories C1, C2,
  • co-cluster pairs of known instances, and text contexts that connect them
### Example Discovered Relations

[Mohamed et al. *EMNLP 2011*]

<table>
<thead>
<tr>
<th>Category Pair</th>
<th>Text contexts</th>
<th>Extracted Instances</th>
<th>Suggested Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>MusicInstrument Musician</td>
<td>ARG1 master ARG2 ARG1 virtuoso ARG2 ARG1 legend ARG2 ARG2 plays ARG1</td>
<td>sitar, George Harrison tenor sax, Stan Getz trombone, Tommy Dorsey vibes, Lionel Hampton</td>
<td>Master</td>
</tr>
<tr>
<td>Disease Disease</td>
<td>ARG1 is due to ARG2 ARG1 is caused by ARG2</td>
<td>pinched nerve, herniated disk tennis elbow, tendonitis blepharospasm, dystonia</td>
<td>IsDueTo</td>
</tr>
<tr>
<td>CellType Chemical</td>
<td>ARG1 that release ARG2 ARG2 releasing ARG1</td>
<td>epithelial cells, surfactant neurons, serotonin mast cells, histamine</td>
<td>ThatRelease</td>
</tr>
<tr>
<td>Mammals Plant</td>
<td>ARG1 eat ARG2 ARG2 eating ARG1</td>
<td>koala bears, eucalyptus sheep, grasses goats, saplings</td>
<td>Eat</td>
</tr>
<tr>
<td>River City</td>
<td>ARG1 in heart of ARG2 ARG1 which flows through ARG2</td>
<td>Seine, Paris Nile, Cairo Tiber river, Rome</td>
<td>InHeartOf</td>
</tr>
</tbody>
</table>
NELL: recently self-added relations

- athleteWonAward
- animalEatsFood
- languageTaughtInCity
- clothingMadeFromPlant
- beverageServedWithFood
- fishServedWithFood
- athleteBeatAthlete
- athleteInjuredBodyPart
- arthropodFeedsOnInsect
- animalEatsVegetable
- plantRepresentsEmotion
- foodDecreasesRiskOfDisease
- clothingGoesWithClothing
- bacteriaCausesPhysCondition
- buildingMadeOfMaterial
- emotionAssociatedWithDisease
- foodCanCauseDisease
- agriculturalProductAttractsInsect
- arteryArisesFromArtery
- countryHasSportsFans
- bakedGoodServedWithBeverage
- beverageContainsProtein
- animalCanDevelopDisease
- beverageMadeFromBeverage
Key Idea 4: Cumulative, Staged Learning

Learning X improves ability to learn Y

1. Classify noun phrases (NP’s) by category
2. Classify NP pairs by relation
3. Discover rules to predict new relation instances
4. Learn which NP’s (co)refer to which concepts
5. Discover new relations to extend ontology
6. Learn to infer relation instances via targeted random walks
7. Learn to assign temporal scope to beliefs
8. Learn to microread single sentences
9. Vision: co-train text and visual object recognition
10. Goal-driven reading: predict, then read to corroborate/correct
11. Make NELL a conversational agent on Twitter