An Introduction to Entity Recommendation and Understanding

Hao Ma and Yan Ke
Microsoft
The contents and opinions described in this tutorial do not necessarily reflect the opinions of Microsoft.

Technologies mentioned might or might not be in actual use.
Goals of this Tutorial

• Help identify many interesting applications in the field of Entity Recommendation and Understanding

• Present the current state of research on related topics

• Pinpoint challenging research problems
Outline

• Introduction to Entity and Knowledge
• Demonstration of Microsoft’s Entity Experience
• Entity Recommendation and Understanding
  – $P(\text{entity}|\text{entity})$
  – $P(\text{entity}|\text{user})$
  – $P(\text{entity}|\text{query})$
• Summary
Outline

• Introduction to Entity and Knowledge

• Demonstration of Microsoft’s Entity Experience

• Entity Recommendation and Understanding
  – $P(\text{entity}|\text{entity})$
  – $P(\text{entity}|\text{user})$
  – $P(\text{entity}|\text{query})$

• Summary
Introduction to Entity and Knowledge
Why “Entities”

Florence - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Florence
Florence is the capital city of the Italian region of Tuscany and of the province of Florence. It is the most populous city in Tuscany, with approximately 380,000...

TripAdvisor Florence - Travel & Tourism for Florence, Italy
www.tripadvisor.com/...Italy>Tuscany>Province of Florence>
Florence Tourism. TripAdvisor has 565,444 reviews of Florence Hotels, Attractions, and Restaurants making it your best Florence resource.

Florence, Italy: Tourist Travel Guide for Holidays in...
www.visitflorence.com
Visit Florence, one of the most beautiful cities in Italy and center of Italian Renaissance. Our travel guide helps you plan your holidays in Florence, Italy.

News about Florence
bing.com/news
Florence Welch broke her foot at Coachella
USA Today - 23 hours ago
Florence Welch of Florence + the Machine performs at the 2015 Coachella festival. (Photo: Scott Roth, Invision/AP) Captivating the Coachella crowd can cost...

Florence Welch breaks her foot after jumping off Coachella stage
New York Daily News - 2 hours ago
Florence Welch Breaks Foot At Coachella, Strips Rack, Performances The Inquisitor - 21 hours ago

Florence places to go

Best Places to Visit in Florence, Italy | The Duomo...
www.thereareplaces.com/newguidebook/pdest/ftfonpts.htm
The Best Places to Visit In Florence described above include the most popular tourist attractions in Firenze. Florence offers great restaurants, yummy gelato shops...

Top Sights and Attractions in Florence, Italy
gotitaly.about.com/...What to See In Florence>
Here are the top must-see places and tourist attractions in Florence. Find out what to see and do on your visit to Florence, Italy.

Places to visit in Florence - Andreea Francu
andreea.francu.com/travel/florence/it/places/it
Places to visit in Florence... In the front of the church is a good place for taking a break. Rest on the steps in front of Dante's statue and watch the world go by.

Top 19 Places to Visit in Florence: Check out Florence...
www.tripadvisor.in/...South Carolina (SC)>Florence>
Top 15 places to visit in Florence, South Carolina. See TripAdvisor's 100 traveller reviews and photos of Florence attractions.

The Shoals, Alabama - Places To Go, Restaurants and...
alabama.travel/places-to-go/the-shoals>
The Shoals area of Alabama is the birthplace of some of America's most influential music. Explore Florence. Muscle Shoals and Helen Keller's childhood...

Things to do in Florence with kids - KY on FAMILYdaysOUT...
Fun things to do in Florence for kids - Kentucky - all colour coded by category - great places to go with children and family attractions to visit - preschoolers play

ending, F
Why “Entities”

Cities near Florence, Italy - Travelmath
www.travelmath.com/cities-near/Florence
What are some other cities, towns, and suburbs near Florence, Italy? Find the closest city and explore the surrounding area.

11 Reviews of Cities Not to Miss Near Florence in Florence
www.virtualtourist.com / Italy / Tuscany / Florence / Favorites
Cities Not to Miss Near Florence Florence tips from real travelers and locals in Florence, Italy

Cities near Florence, Kentucky - Travelmath
www.travelmath.com/cities-near/Florence, KY
What are some other cities, towns, and suburbs near Florence, KY? Find the closest city and explore the surrounding area.

List of Cities near Florence in Toscana, Italy - GoMapper
The closest cities, towns, suburbs/localities and places to Florence in Toscana, Italy are listed below in order of increasing distance.

Cities and Towns near Florence | MyTravelGuide.com
www.mytravelguide.com > Attractions
Cities and towns near Florence - MyTravelGuide - Reviews and research on all Hotel Restaurants and more. Plan your next trip at MyTravelGuide.

Florence, Oregon - Official Site
www.ci.florence.or.us
Offers information on city government, services, business development, and departments. Includes news, events, calendar, city code, meeting minutes, and resource links.
Why “Entities”

Florence - Wikipedia, the free encyclopedia
e.n.wikipedia.org/wiki/Florence
Florence is the capital city of the Italian region of Tuscany and of the province of Florence. It is the most populous city in Tuscany, with approximately 380,000 inhabitants, expanding to over 1,620,000 in the metropolitan area.

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Florence.it: Tourist Travel Guide for Holidays in...
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Visit Florence, one of the most beautiful cities in Italy and center of Italian Renaissance. Our travel guide helps you plan your holidays in Florence, Italy.

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Florence Welch broke her foot at Coachella
USA Today - 23 hours ago
Florence Welch of Florence + the Machine performs at the 2015 Coachella festival. (Photo: Scott Roth, Invasion/AP) Captivating the Coachella crowd can cost...

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New York Daily News - 2 hours ago
Florence Welch Breaks Foot At Coachella. ‘Strips Back’ Performances
The Inquisitr - 21 hours ago

Florence
City
Florence is the capital city of the Italian region of Tuscany and of the province of Florence. It is the most populous city in Tuscany, with approximately 380,000 inhabitants, expanding to over 1,620,000 in the metropolitan area.
en.wikipedia.org
Local time: 9:12 PM 4/16/2015
Area: 36.54 sq miles (102.41 km²)
Explore area: Florence - Tuscany - Italy
Travel tip: Everyone’s heard the Doors of Paradise, the Duomo, +
Colleges and universities: University of Florence - Accademia di Belle Arti di Firenze - European University Institute - Accademia Italiana +

Weather
59 °F Patchy fog
H:79 °F L:53 °F

Points of interest

People also search for
Venice - Rome - Milan - Pisa - Naples
Why “Entities”

One single Entity Pane can answer many user queries and satisfy users’ diverse information needs.
Why “Entities”
Why “Entities”
Because Entities are Surrounded by Knowledge
Why People Search?
Our Job
Entity Graphs

Knowledge Graph

Satori Knowledge Base

Freebase

DBpedia

yago

select knowledge
Entity Definition
Knowledge Definition

**NFL championships:** 2013
**Head coach:** Pete Carroll
**Founded:** 1976
**Division:** NFC West

**Address:** 400 Broad St, Seattle, 98109
**Phone:** (800) 937-9582
**Opened:** Apr 21, 1962
**Height:** 605 feet (184.41 m)
**Floors:** 6

**Population:** 652,405 (2013)
**Area:** 142.55 sq miles (369.20 km²)
**Mayor:** Ed Murray

**Founded:** Mar 30, 1971 · Pike Place Market
**Customer service:** +1 800-782-7282
**CEO:** Howard Schultz
**Founders:** Jerry Baldwin · Zev Siegl · Gordon Bowker

Entity Graphs
Why “Entity Recommendation”

• Information Explosion
Why “Entity Recommendation”
Why “Entity Recommendation”

- Information Overload

Help Explore the Knowledge Base
Why “Entity Recommendation”
Why “Entity Recommendation”
Why “Entity Recommendation”
Why “Entity Understanding”

- Knowledge Bases are just an unordered list of facts
Why “Entity Understanding”

• Knowledge Bases are just an unordered list of facts

• Understanding is
  – Ranking facts
  – Creating connections between entities
  – Connecting entities and facts to queries and documents
Why “Entity Understanding”

- When a user typed “Florence”, how do you know which “Florence”?
Why “Entity Understanding”

• When a user typed “how tall is he”, how do you know who is “he”?

How Tall is Tom Cruise

News about Tom Cruise

HEAR IT: Tom Cruise ‘funds the church’ PL on Scientology payroll tells cops
New York Daily News - 4 hours ago
There’s no mission impossible for Scientologists. Tom Cruise is such a force for Scientology that followers believe the action movie star bankrolls much of the church’s …
Why “Entity Understanding”

• When a user typed “how tall is he”, how do you know who is “he”?

[Image of a search result showing Tom Cruise's height as 5' 7" (1.70 m)]
Why “Entity Understanding”

• When a user clicked a few Web pages, how do you know what kind of entities this user is interested in?
Technologies

• Natural Language Processing
• Machine Learning
• Information Retrieval
• Recommender Systems
• Text and Log Mining
• ......
Data Sources

• Wikipedia
  – Semi-structured free Internet encyclopedia, contributed by community members

• Freebase
  – Structured data composed mainly by its community members
  – Acquired by Google on July 2010, and will be retired on June 2015
  – Data will be ported to WikiData

• WikiData
  – a collaboratively edited knowledge base

• DBPedia
  – Extracted structured information from Wikipedia

• Yago
  – a knowledge base automatically extracted from Wikipedia and other sources
  – Accuracy 95.02% based on manual evaluation

• Web Documents
• Queries and Search Click Log
Applications

• Entity Pane Experiences
• Entity Recommendation
  – Recommendation and Ranking
  – Interpretation
  – Exploration
  – Personalization
• Factoid Answers
• Graph Search
• Conversational Question and Answering
• Natural Language Question and Answering
• ... ...
Outline

• Introduction to Entity and Knowledge
• Demonstration of Microsoft’s Entity Experience
• Entity Recommendation and Understanding
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Demonstration of Microsoft’s Entity Experience
Entities are deeply integrated

• Bing
  – SERP, Images, Videos, Maps, ...
• Office
• Windows
• Edge Browser
• Phone
• Xbox
Integrated Entity Experiences

• Combine data from many sources for an entity to build a rich user experience.
With or Without You

"With or Without You" is a song by the Irish rock band U2. It is the third track from their fifth studio album, The Joshua Tree, and was released as the album's lead single on 21 March 1987. The song was the group's most successful single at that time.

Wikipedia, the free encyclopedia

"With or Without You" is a song by the Irish rock band U2. It is the third track from their fifth studio album, The Joshua Tree (1987), and was released as the album's lead single on 21 March 1987. The song was the group's most successful single at that time.

With or Without You Lyrics - U2 - LyricsFreak.com

Lyrics to With or Without You by U2: See the stone set in your eyes / See the thorn twist in your side / I'll wait for you / Sleight of hand

Related searches for u2 with or without you

U2 All I Want Is You
U2 Greatest Hits
With or Without You Lyrics
With or Without You U2 YouTube
With or Without You Song

U2 - With or Without You Lyrics | MetroLyrics

"With or Without You" is track #4 on the album U218 Singles. It was written by Adam Clayton, Dave Evans, Paul Hewson, Larry Mullen. (No other information is available...)

Also appears on

U218 The Best Of Please Singles 1980 - 1990

Data from: Xbox Music - LyricFind - Freebase
TED talks

- Teachers need real feedback
- Mosquitos, malaria and education
- How state budgets are breaking US schools
- Why giving away our wealth has been the most satisfi...
Timeline

1973: Gates enrolled in Harvard College where he met Steve Ballmer who would later succeed him as a CEO of Microsoft. In college, Gates did not have a proper study plan, used most of his time using the school’s computer and demonstrated potential for solving hard problems. He left eventually two years later to start a company.

1975: What started as a project for demonstrating Altair emulator, Microsoft was formed as a partnership between Paul Allen and Bill Gates and had their first office located in Albuquerque.

1985: Under Gates, MS launches Microsoft Windows which became the dominant OS. In the next few years, Microsoft Office was launched which was eventually used by over a billion people. These two product lines largely defined the success of Microsoft and Bill Gates as a CEO.

See more ▼
Online Courses

Stanford University

Stanford University is a private research university in Stanford, California, and one of the world's most prestigious institutions, with the highest undergraduate selectivity and the top position in numerous surveys and measures in the Unite... en.wikipedia.org

Address: 450 Serra Mall, Stanford, CA 94305
Ranking: #4 National University (2015)
Acceptance rate: 5.70% (2015)
Tuition: $43,245 USD (2015)
Founded: Oct 01, 1891

Popular online courses

- Machine Learning
- Natural Language Processing
- Child Nutrition and Cooking 2.0
- Automata
- Game Theory

Physics

Physics is the natural science that involves the study of matter and its motion through space and time, along with related concepts such as energy and force. More broadly, it is the general analysis of nature, conducted in order to understand h... en.wikipedia.org

Subdiscipline of: Natural science

Popular online courses

- Calculating average velocity or speed
- Relationship between angular velocity and speed
- Displacement from time and velocity example
- Inclined plane force components
- Balanced and unbalanced forces

See more

Subdisciplines

- Astronomy
- Quantum mechanics
- Mechanics
- Nuclear physics
- Particle physics

See all (10+)
Long tail of interconnected entities
Actions – facilitate task completion
The Avengers

PG-13 · 2hr 23min · Sci-Fi

IMDb 8.2/10 ★★★★★
Rotten Tomatoes 92% ★★★★★

"Marvel's The Avengers"- the Super Hero team up of a lifetime, featuring iconic Marvel Super Heroes Iron Man, The Incredible Hulk, Thor, Captain America, Hawkeye and Black Widow. When an unexpected enemy emerges that threatens global safety and security, Nick Fury, Director of the international peacekeeping agency known as S.H.I.E.L.D., finds himself in need of a... +

Estimated budget: $220 million USD
Release date: May 04, 2012
Director: Joss Whedon
Sequel: Avengers: Age of Ultron
Production company: Marvel Studios
Story by: Joss Whedon · Zak Penn

Watch now
- Netflix
- Amazon
- Xbox Video
- Watch trailer on IMDb

Songs of Innocence (2014)

Songs of Innocence is the thirteenth studio album by Irish rock band U2. Released on 9 September 2014, it was produced by Danger Mouse, with additional production from Paul Epworth, Ryan Tedder, Declan Gaffney and Flood. The albu... +

Genre: Rock, Mainstream Rock
Label: Interscope
Release year: 2014
Artist: U2

Listen or buy
- Xbox Music
- iTunes
El Gaucho
elgaacho.com
450 108th Avenue NE, Bellevue, WA 98004 • 6.31 mi
(425) 455-2715
Open 11:30 AM - 10:00 PM
347 Yelp reviews • $$$$$
Demonstration of Microsoft’s Entity Experience

Question Answering
First movie of Tom Hanks starring Meg Ryan

Joe Versus the Volcano (1990)
Director of first movie of Tom Hanks starring Meg Ryan

John Patrick Shanley

Joe Versus the Volcano (1990) - IMDb
www.imdb.com/title/tt0099892
★★★★★ Rating: 5.7/10 · 25,640 ratings · Comedy/Romance · PG · 102 min
Joe Versus the Volcano PG ... Director: John Patrick Shanley. Writer: John Patrick Shanley. Stars: Tom Hanks, Meg Ryan, Lloyd Bridges | See full cast and crew »

Meg Ryan Reteams With Tom Hanks for Ithaca , Actress Set ...
www.eonline.com/news/505216/meg-ryan-reteams-with-tom-hanks-for... ➤
Jan 29, 2014 · Meg Ryan and Tom Hanks are teaming ... latest to step into the role of director. ... and was instrumental in making the first film such a...
Conversational Question Answering

http://blogs.bing.com/search/2014/08/13/lets-have-a-conversation/
who was he married to

262,000 RESULTS  Any time

Tom Cruise spouse
Katie Holmes
(m. 2006-2012)

Nicole Kidman
(m. 1990-2001)

Mimi Rogers
(m. 1987-1990)

Find out more on: wikipedia
Katie Holmes height: 5 feet 9 inches (1.75 meters)
Nicole Kidman height: 5 feet 11 inches (1.80 meters)
Mimi Rogers height: 5 feet 9 inches (1.74 meters)

Find out more on: IMDb
bing

how about nicole

Web Images Videos Maps News More

2,200,000 RESULTS Any time

47 years old
Born Jun 20, 1967
Nicole Kidman · Age

Keith Urban
Spouse
47 years old

Jimmy Fallon
40 years old

Angelina Jolie
39 years old

Data from: Wikipedia
where was she born

Honolulu, HI
Nicole Kidman · Birthplace

Data from: Wikipedia

Nicole Kidman · Biography · IMDb
www.imdb.com/name/nm0000173/bio
48 years old · News
Elegant redhead Nicole Kidman, known as one of Hollywood's top Australian imports, was actually born in Honolulu, Hawaii. Kidman is the daughter of ...
Awards · Films

Nicole Kidman · Biography · Film Actress · Biography.com
www.biography.com/people/nicole-kidman-9364474
Meet Academy Award-winning actress Nicole Kidman at Biography.com. She is best known for movies like Moulin Rouge and her ten-year marriage to Tom Cruise.
Demonstration of Microsoft’s Entity Experience

Diversity of entity collections
Types of Butterflies

- Monarch butterfly
- Swallowtail butterfly
- Morpho
- Papilio glaucus
- Papilio polyxenes
- Pieris rapae
- Limenitis Arthemis
Famous Nebulae

Orion Nebula  Ring Nebula  Crab Nebula  Eagle Nebula  Heart Nebula  Horsehead Nebula  Helix Nebula
Republican Party United States President

Abraham Lincoln
1861 - 1865

Theodore Roosevelt
1901 - 1909

George W. Bush
2001 - 2009

Dwight D. Eisenhower
1953 - 1961

Richard Nixon
1969 - 1974

George H. W. Bush
1989 - 1993

Ulysses S. Grant
1869 - 1877
Ivy league schools

- Brown University
- Columbia University
- Cornell University
- Dartmouth College
- Harvard University
- Princeton University
- University of Pennsylvania
- Yale University
Segment-specific entity rankings
Demonstration of Microsoft’s Entity Experience

Entities in the platform
Bing Predicts

American Idol
Search for “American Idol predictions” to find out who Bing predicts will be eliminated and who'll be safe.

Dancing with the Stars
Search for “Dancing with the Stars predictions” to see who Bing predicts will make it to the next round and who won’t.

https://www.bing.com/explore/predicts
Bing Predicts

March Madness
Prediction accuracy: 73 percent

American Idol
Prediction accuracy: 90 percent

Dancing with the Stars
Prediction accuracy: 95 percent

The Voice
Prediction accuracy: 85 percent

Academy Awards
Prediction accuracy: 84 percent

Golden Globe Awards
Prediction accuracy: 83 percent
Bing Widget API

http://blogs.bing.com/webmaster/2014/01/03/bringing-the-power-of-bing-knowledge-to-webmasters/
http://blogs.bing.com/webmaster/2014/05/15/mark-it-up/
App Linking

http://www.bing.com/webmaster/help/app-linking-09399b4b
App Linking
Abraham Lincoln was the 16th president of the United States and was born in

http://blogs.office.com/2014/12/10/whats-new-office-online/
The Corps of Discovery departed from Camp Dubois at 4 pm on May 14, 1804, and met up with Lewis in St. Charles, Missouri, a short time later, marking the beginning of the voyage to the Pacific coast. The Corps followed the Missouri River westward. Soon, they passed La Charrette, the last Euro-American settlement on the Missouri River.

(Source: [http://en.wikipedia.org/wiki/Lewis_and_Clark_Expedition](http://en.wikipedia.org/wiki/Lewis_and_Clark_Expedition))
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(Source: [http://en.wikipedia.org/wiki/Lewis_and_Clark_Expedition](http://en.wikipedia.org/wiki/Lewis_and_Clark_Expedition))
Edge Browser

Is the **Seahawk** a Real Bird?

1/31/2014 // By Dace Tinker

My hometown is Portland, Oregon. We do not have a professional football team. I've always loved the Seahawks, but it took me an embarrassingly long time to figure out that they are real. Commonly known as ospreys, these are truly awe-inspiring predators to see in person. I was always fascinated by them. I compiled facts, photos and video in a shameless attempt to convince fans before a very popular football competition this Sunday. Some people may say this is bias, but I know they would be correct.

Fish make up 99% of their diet.

I'm pretty sure the other 1% is brineco.
Is the Seahawk a Real Bird?

http://blog.nwf.org/2014/01/is-the-seahawk-a-real-bird/
Phone / Cortana

Windows

http://blogs.bing.com/search/2013/10/18/unwrapping-windows-8-1-bing-smart-search/
Windows
Xbox

http://blogs.bing.com/search/2013/11/19/xbox-bing-deliver-me-a-whole-new-way-to-search/
Challenges

• Speed – entity search can’t slow down web search.
• Size – serve hundreds of millions of entities online.
• Generalize to tail – how to retrieval and recommend tail entities when there are no popularity signals.
• Ambiguity – how to ask users to clarify intent.
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Entity Recommendation and Understanding
Traditional Recommender Systems
Traditional Recommender Systems

- Recommender Systems have been well studied from many aspects
  - Collaborative filtering
  - Content-based
  - Context-aware
  - Rating-based
  - Learning to Rank
  - Diversity
  - Serendipity
  - Social-Aware
  - Temporal
  - Explore/Exploit
  - ... ...
Traditional Recommender Systems

• Majority of the algorithms is focusing on Personalization
  – $P(item|user)$
  – User-Item Matrix

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Entity Recommender Systems

- **Entity Graph**
  - Heterogeneous Graph
  - Freebase
  - 2K+ commonly used types
  - 30K+ commonly used properties

```
NFL championships: 2013
Head coach: Pete Carroll
Founded: 1976
Division: NFC West

Address: 400 Broad St, Seattle, 98109
Phone: (800) 937-9582
Opened: Apr 21, 1962
Height: 605 feet (184.41 m)
Floors: 6

Population: 652,405 (2013)
Area: 142.56 sq miles (369.20 km²)
Mayor: Ed Murray
```

- **Seattle**
  - Location
  - Home Field
  - Headquarters
Entity Recommender Systems

- Entity Graph
  - Hugh Size
  - Freebase
  - 47M+ topics
  - 2.9B+ facts
Entity Recommender Systems

- Non-Personalized
  - $P(item|item)$
  - $P(item|query)$

Collaborative filtering

Collaborative filtering is a technique used by some recommender systems. Collaborative filtering has two senses: a narrow one and a more general one. In general, collaborative filtering for information or pat...
Entity Recommender Systems

- Personalization
  - $P(item|user)$
Entity Recommender Systems in Search

- Recommendation & Ranking
- Interpretation
- Entity Collection Recommendation
- Exploration
- Personalization
Golden Gate Bridge

The Golden Gate Bridge is a suspension bridge spanning the Golden Gate strait, the mile-wide, three-mile-long channel between San Francisco Bay and the Pacific Ocean. The structure links the U.S. city of San Francisco, on the northern tip of the San Francisco Peninsula, to Marin County, bridging both U.S. Route 101 and California State R...+

Charles Alton Ellis was a professor, structural engineer and mathematician who was chiefly responsible for the structural design of the Golden Gate Bridge.

Harvard University

Harvard University is a private Ivy League research university in Cambridge, Massachusetts, whose history, influence and wealth have made it one of the most prestigious universities in the world. Established in 1636 by the Massachusetts legislature and soon thereafter named for John Harvard, Harvard is the United States' o...+

Related people

John Harvard
Founder

Drew Gilpin Faust
President

Mark Zuckerberg
Alumni

Barack Obama
Alumni

Bill Gates
Alumni

Born in Honolulu, Hawaii, Barack Obama is a graduate of Columbia University and Harvard Law School, where he was president of the Harvard Law Review.
Entity Collection Recommendation

[Image of search results for Tom Hanks' dramas and romance movies]
Exploration

Die Hard (1988)

Die Hard is a 1988 American action film directed by John McTiernan and written by Steve de Souza and Jeb Stuart, based on the 1979 novel Nothing Lasts Forever by Roderick Thorp. Die Hard follows off-duty New York City Police Department off...
Entity Recommendation & Understanding

Taxonomy

• $P(item|item)$
  – Recommendations given an item

• $P(item|user)$
  – Recommendations given a user

• $P(item|query)$
  – Recommendations given a query
Entity Recommendation & Understanding

Taxonomy

- $P(entity|entity)$
  - Recommendations given an entity

- $P(entity|user)$
  - Recommendations given a user

- $P(entity|query)$
  - Recommendations given a query
\[ P(\text{entity}|\text{entity}) \]

- \[ P(\text{Florence}|\text{Italy}) = \frac{\text{Freq}(\text{Florence, Italy})}{\text{Freq}(\text{Italy})} \]
- \[ P(\text{Florence}|\text{Italy}) = \frac{\text{Sim}(\text{Florence, Italy})}{\sum \text{Sim}(\text{*, Italy})} \]
\( P(\text{entity}|\text{entity}) \) – Co-occurrence

• Sources
  – Within Queries
  – Across Queries
  – User Url Clicks
  – Wikipedia Pages
  – Wikipedia Categories/Templates
  – Wikipedia Revision Histories
  – Web documents
  – ... ...

The Wisdom of Crowds
$P(entity|entity)$ – Co-occurrence

- Within Queries

How to extract those entities?

Entity Recommendations in Web Search [Roi Blanco, et al., ISWC 2013]
$P(\text{entity}|\text{entity})$ – Co-occurrence

- Across Queries

Entity Recommendations in Web Search [Roi Blanco, et al., ISWC 2013]
$P(\text{entity}|\text{entity})$ – Co-occurrence

- User Url Clicks

\[ P(\text{entity} | \text{entity}) - \text{Co-occurrence} \]

- Wikipedia Pages
$P(entity|entity)$ – Co-occurrence

– Wikipedia Pages

An Effective, Low-Cost Measure of Semantic Relatedness Obtained from Wikipedia Links [David Milne, et al., AAAI 2008]
P(entity|entity) – Co-occurrence

- Wikipedia Pages
  - Direct Link
  - Shared Link
  - Shared Backlink
  - Directed Path

$P(\text{entity} | \text{entity})$ – Co-occurrence

– Wikipedia Categories & Templates

\[ P(\text{entity} | \text{entity}) \text{ – Co-occurrence} \]
\( P(\text{entity} | \text{entity}) \) – Co-occurrence

- Web documents
  - Moon
  - John F. Kennedy
  - United States
  - NASA
  - Apollo 11
  - Neil Armstrong
  - Edwin “Buzz” Aldrin
  - Michael Collins
  - Astronauts

**\( P(\text{entity} | \text{entity}) \) – Co-occurrence**

- Entity Recommendations based on Wikipedia Co-occurrence

<table>
<thead>
<tr>
<th>Whale</th>
<th>Susan Dumais</th>
<th>Tom Cruise</th>
<th>Susan Dumais</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dolphin</td>
<td>C. J. van Rijsbergen</td>
<td>Nicole Kidman</td>
<td>Latent semantic analysis</td>
</tr>
<tr>
<td>Pinniped</td>
<td>W. Bruce Croft</td>
<td>Brad Pitt</td>
<td>Information retrieval</td>
</tr>
<tr>
<td>Shark</td>
<td>Eric Horvitz</td>
<td>Steven Spielberg</td>
<td>Gerard Salton Award</td>
</tr>
<tr>
<td>Killer whale</td>
<td>George Furnas</td>
<td>Tom Hanks</td>
<td>SIGIR</td>
</tr>
<tr>
<td>Humpback whale</td>
<td>Thomas Landauer</td>
<td>John Travolta</td>
<td>Singular value decomposition</td>
</tr>
</tbody>
</table>
Entity Linking

• How to extract entities from Queries and Documents?
  – Through Entity Linking!

Entity linking

In natural language processing, entity linking, named entity disambiguation, named entity recognition and disambiguation or named entity normalization is the task of determining the identity of entities mentioned in text. It is distinct from named entity recognition in that it identifies not the occurrence of names, but their reference.

en.wikipedia.org


People also search for

Information extraction
Question answering
Natural language processing
Explicit semantic analysis
Automatic summarization

See more →
The First Person on the Moon

It was 1961. John F. Kennedy was the president of the United States. He wanted to land humans on the moon. The United States had just started trying to put people in space. Was NASA ready to go to the moon? The president and NASA knew they could do it. They were ready to put people on the moon. Apollo 11’s mission was to land two men on the moon. They also had to come back to Earth safely.

Apollo 11 blasted off on July 16, 1969. Neil Armstrong, Edwin "Buzz" Aldrin and Michael Collins were the astronauts on Apollo 11.
Entity Linking - Main Problem

• Linking free text to entities
  – Any piece of text
    ▫ News document
    ▫ Blog posts
    ▫ Tweets
    ▫ Queries
    ▫ …

• Entities taken from a knowledge base
  – Freebase
  – Wikipedia
  – …

Entity Linking - Common Steps

• Determine “linkable” phrases
  – Mention detection

• Select candidate entity links
  – Link generation
  – May include NILs (null values, i.e., no target in KB)

• Use “context” to disambiguate/filter/improve
  – Disambiguation
Entity Linking

• An Example

**Depth-first search**

From Wikipedia, the free encyclopedia

**Depth-first search (DFS)** is an algorithm for traversing or searching a tree structure or graph. One starts at the root (selecting some node as the root in the graph case) and explores as far as possible along each branch before backtracking.

Formally, DFS is an uninformed search that progresses by expanding the first child node of the search tree that appears and thus going deeper and deeper until a goal node is found, or until it hits a node that has no children. Then the search backtracks, returning to the most recent node it hadn't finished exploring. In a non-recursive implementation, all freshly expanded nodes are added to a LIFO stack for exploration.

Learning to Link with Wikipedia [David Milne, et al., CIKM 2008]
Public Toolkits for Entity Linking

- Wikipedia Miner
- TagMe
- DBpedia Spotlight
- Illinios Wikifier
- AIDA
- RPI Entity Linking System
$P(\text{entity} | \text{entity})$ - Recap

• Co-occurrence
  – Within Queries
  – Across Queries
  – User Url Clicks
  – Wikipedia Pages
  – Wikipedia Categories/Templates
  – Wikipedia Revision Histories
  – Web documents

• Entity Linking

• Similarity
$P(\text{entity} | \text{entity})$ – Similarity

- TF*IDF scores based on Wikipedia Corpus

**Florence**

From Wikipedia, the free encyclopedia

"Firenze" and "Fiorentine" redirect here. For other uses, see Florence (disambiguation), Fiorentin (disambiguation), (disambiguation).

Florence (/ˈfɪrənsiː/ Italian: Firenze [ˈfɪrɛntse] (listen), alternative obsolete form: Fiesole; Latin: Florentia) is the capital city of the Italian region of Tuscany and of the province of Florence. It is the most populous city in Tuscany, with approximately 380,000 inhabitants, expanding to over 1,520,000 in the metropolitan area. Florence is famous for its history: a centre of medieval European trade and finance and one of the wealthiest cities of the time; it is considered the birthplace of the Renaissance, and has been called "the Athens of the Middle Ages". A turbulent political history includes periods of rule by the powerful Medici family, and numerous religious and republican revolutions. From 1865 to 1871 the city was the capital of the recently established Kingdom of Italy.

The Historic Centre of Florence attracts millions of tourists each year, and Euromonitor International ranked the city as the world's 89th most visited in 2012, with 1.8 million visitors. It was declared a World Heritage Site by UNESCO in 1982. The city is noted for its culture, Renaissance art and architecture and monasteries. The city also contains numerous museums and art galleries, such as the Uffizi Gallery and the Palazzo Pitti, and still exerts an influence in the fields of art, culture and politics. Due to Florence's artistic and architectural heritage, it has been ranked by Forbes as one of the most beautiful cities in the world.

**Rome**

From Wikipedia, the free encyclopedia

This article is about the city in Italy. For the civilization of classical antiquity, see Ancient Rome. For other uses, see Rome (disambiguation). Rome [ɾoːma] (listen), Latin: Roma), is a city and special comune (named "Roma Capitale") in Italy. Rome is the capital of Italy and region of Lazio. With 2.9 million residents in 1,285 km² (496 sq mi), it is also the country's largest and most populated comune and fourth most populous city in the European Union by population within city limits. The Metropolitan City of Rome has a population of 4.3 million residents. The city is located in the central-western portion of the Italian Peninsula, within Lazio (Latium), along the shores of Tiber river. Vatican City is an independent country within the city boundaries of Rome, the only existing example of a country within a city: for this reason Rome has been often defined as capital of two states.

Rome's history spans more than two and a half thousand years. While Roman mythology dates the founding of Rome at only around 753 BC, the site has been inhabited for much longer, making it one of the oldest continuously occupied cities in Europe. The city's early population originated from a mix of Latins, Etruscans and Sabines. Eventually, the city successively became the capital of the Roman Kingdom, the Roman Republic and the Roman Empire, and is regarded as one of the birthplaces of Western civilization. It is referred to as "Roma Aeterna" (The Eternal City) and "Caput Mundi" (Capital of the World), two central notions in ancient Roman culture.
\( P(\text{entity} | \text{entity}) \) – Similarity

- Entity Recommendations based on Wikipedia textual similarity

<table>
<thead>
<tr>
<th>Whale</th>
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</tr>
</thead>
<tbody>
<tr>
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<td>Mark Rathbun</td>
</tr>
<tr>
<td>Humpback whale</td>
<td>Jaime Teevan</td>
<td>L. Ron Hubbard</td>
</tr>
</tbody>
</table>
$P(\text{entity}|\text{entity})$ – Similarity

• Challenges
  – Textual Similarity suffers the vocabulary mismatch problem
    □ “USA” and “United States of America” are semantically equivalent, yet share no terms in common

• Solution
  – Project entities into latent space that can semantically represent the entities
**P(entity|entity) – Word Embedding**

• Word Embedding

\[ s(t) = f(Uw(t) + Ws(t-1)) \]

\[ y(t) = g(Vs(t)) \]

\[ f(z) = \frac{1}{1 + e^{-z}}, \quad g(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}} \]

Figure 1: Recurrent Neural Network Language Model.

Linguistic Regularities in Continuous Space Word Representations [Tomas Mikolov, et al., ACL 2013]
\textbf{P(entity|entity)} – Word Embedding

• Word Embedding

Figure 1: Recurrent Neural Network Language Model.

\textit{Linguistic Regularities in Continuous Space Word Representations [Tomas Mikolov, et al., ACL 2013]}

\( P(\text{entity}|\text{entity}) \) – Word Embedding

- Word Embedding

---

Efficient Estimation of Word Representations in Vector Space [Tomas Mikolov, et al., ICLR 2013]
\( P(\text{entity} | \text{entity}) \) – Word Embedding

Distributed Representations of Words and Phrases and their Compositionality [Tomas Mikolov, et al., NIPS 2013]
### $P(\text{entity}|\text{entity})$ – Word Embedding

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Example 1</th>
<th>Example 2</th>
<th>Example 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>France - Paris</td>
<td>Italy: Rome</td>
<td>Japan: Tokyo</td>
<td>Florida: Tallahassee</td>
</tr>
<tr>
<td></td>
<td>big: bigger</td>
<td>cold: colder</td>
<td>quick: quicker</td>
</tr>
<tr>
<td>Miami - Florida</td>
<td>small: larger</td>
<td>Dallas: Texas</td>
<td>Kona: Hawaii</td>
</tr>
<tr>
<td>Einstein - scientist</td>
<td>Baltimore: Maryland</td>
<td>Mozart: violinist</td>
<td>Picasso: painter</td>
</tr>
<tr>
<td>Sarkozy - France</td>
<td>Messi: midfielder</td>
<td>Merkel: Germany</td>
<td>Koizumi: Japan</td>
</tr>
<tr>
<td>copper - Cu</td>
<td>Berlusconi: Italy</td>
<td>gold: Au</td>
<td>uranium: plutonium</td>
</tr>
<tr>
<td>Berlusconi - Silvio</td>
<td>zinc: Zn</td>
<td>Putin: Medvedev</td>
<td>Obama: Barack</td>
</tr>
<tr>
<td>Microsoft - Windows</td>
<td>Sarkozy: Nicolas</td>
<td>IBM: Linux</td>
<td>Apple: iPhone</td>
</tr>
<tr>
<td>Microsoft - Ballmer</td>
<td>Google: Android</td>
<td>Google: Yahoo</td>
<td>Apple: Jobs</td>
</tr>
<tr>
<td>Japan - sushi</td>
<td>Germany: bratwurst</td>
<td>France: tapas</td>
<td>USA: pizza</td>
</tr>
</tbody>
</table>

Efficient Estimation of Word Representations in Vector Space [Tomas Mikolov, et al., ICLR 2013]
**P**(*entity*|*entity*) – Word Embedding

- How to apply Word Embedding in Entities?
  - Perform entity linking on documents
  - Treat each entity as a single word
  - Learning the representation

**Word2Vec** [Tomas Mikolov, et al., ICLR 2013]
**P(entity|entity) – Word Embedding**

- Entity Recommendations based on Word Embedding (Skip-gram)
- Trained on 100M Google News Articles

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</tr>
<tr>
<td>Turtle</td>
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<td>Cameron Diaz</td>
</tr>
<tr>
<td>Rat</td>
<td>Richard Rashid</td>
<td>Connor Antony</td>
</tr>
</tbody>
</table>

Word2Vec [Tomas Mikolov, et al., ICLR 2013]
\[ P(\text{entity} | \text{entity}) \]

- Co-occurrence and Textual Similarity methods work well

- Textual Similarity method is very topic- or genre-related

- Word Embedding might not always work (depend on training data)

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**Co-occurrence**

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**Textual Similarity**

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**Word Embedding**
$P(\text{entity}|\text{entity})$ - Recap

• Co-occurrence
  – Within Queries
  – Across Queries
  – User Url Clicks
  – Wikipedia Pages
  – Wikipedia Categories/Templates
  – Wikipedia Revision Histories
  – Web documents

• Entity Linking

• Similarity
  – Textual Similarity
  – Word Embedding

• Interpretation
Why are they related to “Florence Cathedral”?
Florence Cathedral

Church

The Cattedrale di Santa Maria del Fiore is the main church of Florence, Italy. Il Duomo di Firenze, as it is ordinarily called, was begun in 1296 in the Gothic style to the design of Arnolfo di Cambio and completed structurally in 1436 with the dome … en.wikipedia.org

Opened: Mar 25, 1436
Height: 376 feet (114 50 m)
Architects: Filippo Brunelleschi - Giotto - Arnolfo di Cambio - Francesco Talenti
Architectural styles: Renaissance architecture - Gothic architecture - Italian Gothic architecture - Gothic Revival architecture
Categories: Basilica - Cathedral - Minor basilica - Church
Burials: Filippo Brunelleschi - Conrad II of Italy - Niccolò da Tolentino

Related people

Filippo Brunelleschi Architect
Michelangelo Donatello Giotto Architect Arnolfo di Cambio Architect

P(entity|entity) - Interpretation

Hyatt

Company

Hyatt Hotels Corporation is an American international company and operator of hotels. The Hyatt Corporation came into being upon purchase of the Hyatt House, at Los Angeles International Airport, on September 27, 1957. In 2014, Fort… en.wikipedia.org

Founded: 1957
CEO: Mark Hoplamazian
Founders: Jack D. Crouch - Hyatt von Dehn
Headquarters: Chicago, Il

Related people

Liesel Pribber Simmons, stage name Liesel Matthews, is an American former child actress, heiress to the Hyatt Hotels fortune, and philanthropist.
\( P(entity|entity) \) - Interpretation

- Problem definition

<table>
<thead>
<tr>
<th>Notation</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>( e_a )</td>
<td>the first entity of the entity pair.</td>
</tr>
<tr>
<td>( e_b )</td>
<td>the second entity of the entity pair.</td>
</tr>
<tr>
<td>( r )</td>
<td>the relation of interest between ( e_a ) and ( e_b ).</td>
</tr>
<tr>
<td>( S )</td>
<td>a set of candidate sentences possibly referring to ( e_a ) and ( e_b ).</td>
</tr>
</tbody>
</table>

Explaining Relationships Between Entities [Nikos Voskarides]
$P(\text{entity} | \text{entity})$ - Interpretation

• Entity text representation

Wikipedia Title: Barack Obama
Wikipedia Anchor: President obama
Wikipedia Redirect: Obama

Wikipedia Title: Bill Clinton
Wikipedia Anchor: Clinton
Wikipedia Redirect: President clinton

Explaining Relationships Between Entities [Nikos Voskarides]
\[ P(\text{entity}|\text{entity}) \] - Interpretation

- **Candidate Sentences**
  - On the wiki pages of “Barack Obama” and “Bill Clinton”
  - Keep those sentences that contains at least one entity’s text representations

Explaning Relationships Between Entities [Nikos Voskarides]
$P(\text{entity}|\text{entity})$ - Interpretation

- Sentences enrichment
  - Perform Co-reference resolution
  - Replace detected strings with the entity text representations
  - Examples:
    - “He” $\rightarrow$ Barack Obama
    - “The company” $\rightarrow$ Toyota
    - “The film” $\rightarrow$ Titanic
In response to the 2010 Haiti earthquake, U.S. President Barack Obama announced that Clinton and George W. Bush would coordinate efforts to raise funds for Haiti’s recovery.
\[ P(\text{entity} | \text{entity}) \] - Interpretation

• Ranking sentences
  – Generate features and using Learning to Rank algorithms to rank sentences

• Features
  – **Text features**: Average IDF of terms of \( s \) in Wikipedia; Number of terms in \( s \); Part of Speech distribution of \( s \); etc.
  – **Entity features**: Number of entities in \( s \); Whether \( s \) contains links to both \( e_a \) and \( e_b \); Distance between \( e_a \) and \( e_b \) in \( s \); Number of entities between \( e_a \) and \( e_b \); etc.
  – **Relation features**: Whether \( s \) contains any term of \( r \) (binary); Average score of phrases in word2vec(\( r \)) that are matched in \( s \); etc.
  – **Source features**: Position of \( s \) in document \( d \); etc.

Explaining Relationships Between Entities [Nikos Voskarides]
$P(\text{entity}|\text{entity})$ - Interpretation

(#1) Ben Affleck - Bruce Willis (MovieActor_CoCastsWith_MovieActor)

*Affleck starred in “Armageddon” (1998) opposite Bruce Willis.*

(#2) Hugh Jackman - Kate Winslet (MovieActor_CoCastsWith_MovieActor)

*Katie Finneran’s most recent film was “Movie 43” in which she played Angie and also appeared alongside Hugh Jackman and Kate Winslet.*

(#3) Bryan Singer - Tom Cruise (MovieDirector_Directs_MovieActor)

*The film stars Tom Cruise and is directed by Bryan Singer.*

(#4) Cameron Diaz - Tom Cruise (MovieActor_CoCastsWith_MovieActor)

*The following year Cruise starred in the romantic thriller ”Vanilla Sky” (2001) with Cameron Diaz and Penélope Cruz.*

(#5) Cristiano Ronaldo - Karim Benzema (Athlete_PlaysSameSportTeamAs_Athlete)

*Karim Benzema was also shortlisted by the French magazine France Football for the 2008 Ballon d’Or award, won by Cristiano Ronaldo.*

Explaining Relationships Between Entities [Nikos Voskarides]
$P(\text{entity} | \text{entity})$ - Interpretation

- Challenges
  - Relationships are missing or unknown in the real world scenarios
\( P(\text{entity}|\text{entity}) \) - Interpretation

- **Challenges**
  - The selected sentences should be more “interesting” instead of just replicating the relationships

---

(#1) Ben Affleck - Bruce Willis (MovieActor.Co Casts With MovieActor)

*Affleck starred in “Armageddon” (1998) opposite Bruce Willis.*
Entity Recommendation & Understanding

Taxonomy

- \( P(entity|entity) \)
  - Recommendations given an entity
    - Co-occurrence
    - Similarity
    - Entity Linking
    - Interpretation

- \( P(entity|user) \)
  - Recommendations given a user

- \( P(entity|query) \)
  - Recommendations given a query
Entity Recommendation & Understanding

Taxonomy

• \( P(\text{entity} | \text{entity}) \)
  – Recommendations given an entity
    ▫ Co-occurrence
    ▫ Similarity
    ▫ Entity Linking
    ▫ Interpretation

• \( P(\text{entity} | \text{user}) \)
  – Recommendations given a user

• \( P(\text{entity} | \text{query}) \)
  – Recommendations given a query
## Personalized Recommender Systems

### Problem definition
- **User-Item Matrix**

<table>
<thead>
<tr>
<th>Rating/Frequency</th>
<th>Implicit/One-class</th>
</tr>
</thead>
<tbody>
<tr>
<td>( u_1 )</td>
<td>( v_1 )</td>
</tr>
<tr>
<td>( v_1 )</td>
<td>1</td>
</tr>
<tr>
<td>( v_2 )</td>
<td>3</td>
</tr>
<tr>
<td>( v_3 )</td>
<td>4</td>
</tr>
<tr>
<td>( v_4 )</td>
<td>5</td>
</tr>
<tr>
<td>( v_5 )</td>
<td>2</td>
</tr>
</tbody>
</table>

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</tr>
<tr>
<td>( v_1 )</td>
<td>1</td>
</tr>
<tr>
<td>( v_2 )</td>
<td>1</td>
</tr>
<tr>
<td>( v_3 )</td>
<td>1</td>
</tr>
<tr>
<td>( v_4 )</td>
<td>1</td>
</tr>
<tr>
<td>( v_5 )</td>
<td>1</td>
</tr>
</tbody>
</table>
Personalized Recommender Systems

• Memory-based methods
  – Pearson Correlation Coefficient
  – Vector Space Similarity/Cosine Similarity

• Model-based methods
  – Matrix Factorization
  – Probabilistic models
  – Clustering
  – Classification
  – …
Personalized Recommender Systems

• Memory-based methods
  – Pearson Correlation Coefficient
  – Vector Space Similarity/Cosine Similarity

• Model-based methods
  – Matrix Factorization
  – Probabilistic models
  – Clustering
  – Classification
  – …
## Personalized Recommender Systems

- **Memory-based methods**

<table>
<thead>
<tr>
<th>Users</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1$</td>
<td></td>
</tr>
<tr>
<td>$u_2$</td>
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<tr>
<td>$u_5$</td>
<td></td>
</tr>
<tr>
<td>$u_6$</td>
<td>1  3  5  2  4  1  3</td>
</tr>
</tbody>
</table>

Personalized Recommender Systems

- Memory-based methods

<table>
<thead>
<tr>
<th>Users</th>
<th>u₁</th>
<th>u₂</th>
<th>u₃</th>
<th>u₄</th>
<th>u₅</th>
<th>u₆</th>
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<td>3</td>
<td>5</td>
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</tr>
</tbody>
</table>

Personalized Recommender Systems

• Memory-based methods
Personalized Recommender Systems

• Memory-based methods

![User-Item Matrix](image)
### Personalized Recommender Systems

- Memory-based methods

<table>
<thead>
<tr>
<th>Users</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1$</td>
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</tr>
<tr>
<td>$u_2$</td>
<td>1 3 4 2 5 3 4</td>
</tr>
<tr>
<td>$u_3$</td>
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</tr>
<tr>
<td>$u_4$</td>
<td>3 4 3 4 3 4 4</td>
</tr>
<tr>
<td>$u_5$</td>
<td></td>
</tr>
<tr>
<td>$u_6$</td>
<td>1 3 5 2 4 1 3</td>
</tr>
</tbody>
</table>
Personalized Recommender Systems

- Memory-based methods

<table>
<thead>
<tr>
<th>Users</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1$</td>
<td></td>
</tr>
<tr>
<td>$u_2$</td>
<td>1 3</td>
</tr>
<tr>
<td>$u_3$</td>
<td></td>
</tr>
<tr>
<td>$u_4$</td>
<td>3 4 3</td>
</tr>
<tr>
<td>$u_5$</td>
<td></td>
</tr>
<tr>
<td>$u_6$</td>
<td>1 3 5</td>
</tr>
</tbody>
</table>
Personalized Recommender Systems

• Pearson Correlation Coefficient

\[
Sim(a, u) = \frac{\sum_{i\in I(a) \cap I(u)} (r_{a,i} - \bar{r}_a) \cdot (r_{u,i} - \bar{r}_u)}{\sqrt{\sum_{i\in I(a) \cap I(u)} (r_{a,i} - \bar{r}_a)^2} \cdot \sqrt{\sum_{i\in I(a) \cap I(u)} (r_{u,i} - \bar{r}_u)^2}}
\]

Personalized Recommender Systems

• Challenges on using Memory-based methods
  – Sparsity issue
    ▫ User-item matrix is normally very sparse, and the density is normally under 1%
    ▫ The sparsity issue will make estimating user similarity difficult and inaccurate
  – Scalability
    ▫ Finding nearest neighbors require computation that grows with both the number of users and the number of items
Personalized Recommender Systems

• Matrix Factorization

\[ M_{m \times n} = U_{m \times r} V^T_{n \times r} \]
Personalized Recommender Systems

• Matrix Factorization
  – Adding bias
  – $b_{ij} = \mu + b_i + b_j$

  – Predicting rating as
  – $r_{ij} = b_{ij} + u_i v_j^T$

• Matrix factorization method is the single most effective method in the Netflix 1M prize challenge

The Recommender Problem Revisited [Xavier Amatriain, et al., KDD 2014]
Personalized Recommender Systems

- Matrix Factorization
  - What about implicit user-item matrix?
  - Negative Sampling

### Implicit/One-class

<table>
<thead>
<tr>
<th></th>
<th>$v_1$</th>
<th>$v_2$</th>
<th>$v_3$</th>
<th>$v_4$</th>
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<th>$v_6$</th>
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</table>

### Negative Sampling

<table>
<thead>
<tr>
<th></th>
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<th>$v_2$</th>
<th>$v_3$</th>
<th>$v_4$</th>
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<td>0</td>
<td></td>
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</table>

One-Class Collaborative Filtering [Rong Pan, et al., ICDM 2008]
An Incomplete List of Academic Papers on RS

Why is Entity Recommender System different?

• The problem definition for traditional recommender systems is clearer than entity recommender systems since most of the time user-item matrix is given

<table>
<thead>
<tr>
<th></th>
<th>$v_1$</th>
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<th>$v_4$</th>
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<tr>
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<td>1</td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>
Why is Entity Recommender System different?

- Entity recommender systems are embedded within searching process, users’ preferences on entities are more difficult to observe.
Why is Entity Recommender System different?

- The huge Entity Graph with knowledge makes entity recommender systems more challenging and also appealing
$P(\text{entity}|\text{user})$
Current Entity Experience
Current Entity Experience

[Image of a search result for restaurants near Chicago, IL including XOCO, Purple Pig, Portillo's Hot Dogs, Signature Room at the 360th, Quartine, Girl & the Goat, Wildfire, Carmine's, Bandera, and Mercadito.]
P(entity|user)

Movie recommendation for you

- Dallas Buyers Club (2013)
- Inception (2010)
- Finding Mr. Right (2013)
- The Wolf of Wall Street (2013)

Book recommendation for you

- Angels & Demons
- Harry Potter prequel
- The Stand
- Rita Hayworth and The Maiden Thriller

Restaurant recommendation for you

- Shaw's Crab House
- McCormick & Schmick's
- Berghoff Catering & Rehearsal Dinner
- Italian Village

Music album recommendation for you

- Live for Today
- Most Beloved
$P(\text{entity}|\text{user})$

movie recommendation for you

```
THOR
CATCHING FIRE
FROZEN
Gravity
```

restaurant recommendation for you

```
Shaw's Crab house
McCormick & Schmicks
Berghoff Catering & Re...
Italian Village
```

point of interest recommendation for you

```
Shedd Aquarium
Brookfield Zoo
Lincoln Park Zoo
Adler Planetarium
```

event recommendation for you

```
MIAMI HEAT
Wicked
Charles Bradley
Chicago Symphony: Ber...
dec 5th
dec 13th
dec 6th
dec 5th
```
User Logs and Entity Graph

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Problem Definition

- Consider entity related web pages
- User log sequence, sorted by timestamp

\[ < e_1^u, e_2^u, ..., e_t^u, ..., e_{T-1}^u, e_T^u > \]

user log sequence before T, denotes as \( L_T^u \)

- Use \( L_T^u \) to predict \( e_T^u \)

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Benefits in Using User Logs and Entity Graph

• Besides implicit feedback, user log also has
  – e.g., timestamp, dwell time, user country or region, time of day ...

• Cross domain user log events
  – Which movies will foxnews.com readers like?

• Besides entity relationship, entity graph also has
  – e.g., movie release date, tagline, running time, gross revenue, budget, MPAA rating, text description, number of ratings, ...
Exploring data - User interests drift

User interests are consistent within a short time period but drift over time.

The longer the time interval is, the less similar users’ interests are.

Left: accumulated user interest similarity for two weeks
Right: averaged user interest similarity with relative time difference (number of day)

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
## Exploring data - Cross Domain Correlation

<table>
<thead>
<tr>
<th>comicbookresources.com</th>
<th>rueala.com</th>
</tr>
</thead>
<tbody>
<tr>
<td>(comic books)</td>
<td>(women shopping)</td>
</tr>
<tr>
<td>The Avengers</td>
<td>Magic Mike</td>
</tr>
<tr>
<td>Spider-Man</td>
<td>The Avengers</td>
</tr>
<tr>
<td>The Dark Knight Rises</td>
<td>Prometheus</td>
</tr>
<tr>
<td>Prometheus</td>
<td>Prometheus</td>
</tr>
<tr>
<td>Men In Black 3</td>
<td>Moonrise Kingdom</td>
</tr>
<tr>
<td>Iron Man 2</td>
<td>Ted</td>
</tr>
<tr>
<td>Superman: The Man Of Steel</td>
<td>Snow White &amp; Huntsman</td>
</tr>
<tr>
<td>Thor</td>
<td>Savages</td>
</tr>
<tr>
<td>Snow White &amp; Huntsman</td>
<td>Hunger Games</td>
</tr>
<tr>
<td>Battleship</td>
<td>Rock of Ages</td>
</tr>
<tr>
<td></td>
<td>The Best Exotic Marigold Hotel</td>
</tr>
</tbody>
</table>

Top 10 most viewed movies estimated using cross domain correlation

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Entity Pairwise Features

- Meta-path based entity similarity from Freebase
- Entity attribute similarity (e.g., movie description)
- Entity relations derived from user log (e.g., conditional probability)
- Cross domain user log events correlation
- Other pairwise or non-pairwise feature (e.g., popularity)

$S(e_i, e_j)$

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
## Entity Pairwise Features

### Representative Features

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Feature Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Entity Graph Path Features</strong></td>
<td></td>
</tr>
<tr>
<td>movie→actor→movie</td>
<td>movies with the same actors</td>
</tr>
<tr>
<td>movie→director→movie</td>
<td>movies with the same directors</td>
</tr>
<tr>
<td>movie→producer→movie</td>
<td>movies with the same producers</td>
</tr>
<tr>
<td>movie→star→movie</td>
<td>movies with the same stars</td>
</tr>
<tr>
<td>movie→writer→movie</td>
<td>movies with the same writers</td>
</tr>
<tr>
<td>movie→genre→movie</td>
<td>movies with the same genres</td>
</tr>
<tr>
<td>movie→language→movie</td>
<td>movies with the same language</td>
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<tr>
<td><strong>Entity Graph Binary Features</strong></td>
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<tr>
<td>is_prequel</td>
<td>movie1 is a prequel of movie2</td>
</tr>
<tr>
<td>is_sequel</td>
<td>movie1 is a sequel of movie2</td>
</tr>
<tr>
<td>actor→movie</td>
<td>actor appears in the movie</td>
</tr>
<tr>
<td>director→movie</td>
<td>director directs the movie</td>
</tr>
<tr>
<td>producer→movie</td>
<td>producer produces the movie</td>
</tr>
<tr>
<td><strong>Entity Graph Content Features</strong></td>
<td></td>
</tr>
<tr>
<td>release date</td>
<td>two movie with close release dates</td>
</tr>
<tr>
<td>description similarity</td>
<td>text similarity in movie descriptions</td>
</tr>
<tr>
<td><strong>User Log Features</strong></td>
<td></td>
</tr>
<tr>
<td>co_click</td>
<td>conditional probability between entities</td>
</tr>
<tr>
<td>global popularity</td>
<td>movie popularity of all time</td>
</tr>
<tr>
<td>local popularity</td>
<td>movie popularity today</td>
</tr>
<tr>
<td>cross-domain</td>
<td>cross-domain correlation</td>
</tr>
</tbody>
</table>

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Recommendation Models

- Global recommendation model

\[
    r(\hat{e}_T^u; L_T^u, \theta) = \sum_{e_t^u \in L_T^u} w_t(\hat{e}_T^u, e_t^u) \sum_k \theta_k S_k(\hat{e}_T^u, e_t^u)
\]

- entity at timestamp \( T \)
- events happened before \( T \)
- time decay function \( w_t(e_T, e_t) = \beta e^{-\alpha(T-t)} \)
- pairwise features

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Recommendation Models

- Personalized recommendation model \((\text{PRM})\)

\[
 r(\hat{e}^u_T; L^u_T, \theta^u_T) = \sum_{e^u_t \in L^u_T} w_t(\hat{e}^u_T, e^u_t) \sum_{k} S_k(\hat{e}^u_T, e^u_t) \theta^u_{T,k}
\]

For each user at target timestamp \(T\)

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Recommendation Models

• Personalized Recommendation with K-NN (PRM+KNN)

\[ r_n(\hat{e}_t^u ; L_T^u, \theta_T^u) = r(\hat{e}_t^u ; L_T^u, \theta_T^u) + \lambda_1 \sum_{L_T^u \in N(L_T)} w_u(L_T^u) r(\hat{e}_t^u ; L_T^u, \theta_T^u) \]

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Experiment Setup

• Movie recommendation with search engine user log and movie related freebase knowledge graph
  – Sampled 1+ million users with at least one movie entity
  – 2+ million movie related entities with attributes and relationships, including movies, actors/actresses, directors, producers, etc.

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Evaluation

- Top 10 Mean Reciprocal Rank (MRR) as evaluation metric

\[
MRR = \frac{1}{|Test|} \sum_{i=1}^{|Test|} \frac{1}{rank_i}
\]

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Comparison

<table>
<thead>
<tr>
<th>Comparison Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global Popularity</td>
<td>Frequently visited movies in 3 months</td>
</tr>
<tr>
<td>Local Popularity</td>
<td>Frequently visited movies in short time period</td>
</tr>
<tr>
<td>Domain Co-Click</td>
<td>Recommend based on non-movie related events</td>
</tr>
<tr>
<td>Matrix Factorization</td>
<td>Implicit feedback factorization</td>
</tr>
<tr>
<td>Co-Click with Time Decay</td>
<td>Conditional probability of events</td>
</tr>
</tbody>
</table>

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
## Performance

<table>
<thead>
<tr>
<th>Method</th>
<th>MRR</th>
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</thead>
<tbody>
<tr>
<td>Global Popularity</td>
<td>0.024</td>
</tr>
<tr>
<td>Local Popularity</td>
<td>0.043</td>
</tr>
<tr>
<td>Domain Co-click</td>
<td>0.039</td>
</tr>
<tr>
<td>Matrix Factorization</td>
<td>0.160</td>
</tr>
<tr>
<td>Co-Click Time Decay</td>
<td>0.340</td>
</tr>
<tr>
<td>Global Model</td>
<td>0.354</td>
</tr>
<tr>
<td>PRM</td>
<td>0.361</td>
</tr>
<tr>
<td><strong>PRM+KNN</strong></td>
<td><strong>0.451</strong></td>
</tr>
</tbody>
</table>

- **PRM+KNN** utilizes neighbor information when recommending (CF)

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Analysis – Entity Popularity

- Popular movies are easier to predict than other movies
  - Features in recommendation models favor popular movies, e.g.,
    global and local popularity
  - With sufficient training data for popular movies, high quality
    recommendation models can be learned in such scenarios

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Analysis – Number of Neighbors

• The more neighbors each user log sequence has, the better the results
  – More neighbors indicate more data during parameter estimation
  – User log sequences with more neighbors, are usually associated with popular movie entities

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
Analysis – Length of User Log Sequence

• Performance varies with sequence length

On Building Entity Recommender Systems Using User Click Log and Freebase Knowledge [Xiao Yu, et al., WSDM 2014]
$P(\text{entity|user})$ – Conclusion

• It is possible to build a universal recommender system on top of any search engines

• The heterogeneous information in the entity graph can be very helpful in improving the recommendation results
Entity Personalization

• Entity recommender systems - $P(\text{entity}|\text{user})$

[Image of music album recommendation]

• What are other possible entity personalization experiences that are fundamentally different

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Definitions

A User

Main Entity

Related Entities

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Related Entities

• Current recommender:
  – $P(\text{entity}|\text{entity})$
  – $P(\text{Other Movies}|\text{Lincoln})$

• User-specific information is completely ignored

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
User’s information needs are diverse

• Given “Lincoln” movie, a user may be interested in
  – Movies directed by “Steven Spielberg”, or
  – Movies starred by “Daniel Day-Lewis”, or
  – Movies related to “Abraham Lincoln”, or
  – Biographical movies, or
  – Civil War movies, or
  – …..
Related entity personalization

• **Goal**: Given a main entity, we aim to recommend a list of related entities based on the search user’s interest.

• Three important dimensions are involved:

![Diagram showing the process of related entity recommendation](image)

New Paradigm of Recommender Systems

\[ P(\text{entity}|\text{user, entity}) \]

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
User dimension

• User interest patterns can be mined through users’ interactions with the search engine

• Two sources:
  – Search click log
  – Entity pane log

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
User dimension

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  – Entity pane log

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
User dimension

• User interest patterns can be mined through users’ interactions with the search engine

• Two sources:
  – Search click log
  – Entity pane log

<table>
<thead>
<tr>
<th>User ID</th>
<th>Time</th>
<th>Main entity</th>
<th>Related entity</th>
<th>Rank</th>
<th>Click</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>Man of Steel</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>The Wolverine</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>The Lone Ranger</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>498</td>
<td>6/16/2013 15:16:41</td>
<td>Leonardo DiCaprio</td>
<td>Kate Winslet</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>498</td>
<td>6/16/2013 15:16:41</td>
<td>Leonardo DiCaprio</td>
<td>Johnny Depp</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
User dimension

• User interest patterns can be mined through users’ interactions with the search engine

• Two sources:
  – Search click log
  – Entity pane log

• Each user is represented as a vector of features: $\mathbf{x}$
Main entity

- Reflects the user’s current search interest

- Ignoring main entities leads to inferior performance
  - If related entities are obtained based purely on the user’s past interest, they will be completely independent of her information need

- Each main entity is represented as a feature vector: \( y \)
Related entity

• A user may click a related entity, when it is aligned with both her interest pattern and current need

• Clicks on related entities specify user interests in certain facets of the main entities

• Each related entity is represented as a feature vector: 🗭

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Goal

Knowledge base  Search click log  Entity pane log

Three-way Entity Model

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Three-way Entity Model (TEM)

• Trilinear function:

\[ \Phi_{\text{umr}}(\eta) = \sum_{i=0}^{I} \sum_{j=0}^{J} \sum_{k=0}^{K} \eta_{ijk} x_{ui} y_{mj} z_{rk} \]

• Weights capture the associations among users, main entities and related entities

• Feature vectors:

\[ x_u = [1, x_{u1}, x_{u2}, \ldots, x_{uJ}]^T, \]
\[ y_m = [1, y_{m1}, y_{m2}, \ldots, y_{mJ}]^T, \]
\[ z_r = [1, z_{r1}, z_{r2}, \ldots, z_{rK}]^T. \]

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
CTR incorporation

• Trilinear function contributes an important indicator to entity recommendation, especially for rare/new entities

• To further enhance recommendation on popular entities:
  – $\text{CTR}(r)$: CTRs on related entities
  – $\text{CTR}(m, r)$: CTRs on related entities specific to main entity $m$
  – $\text{CTR}(u, m, r)$: CTRs on related entities specific to user $u$ & main entity $m$

• Integration:

\[
\Psi_{umr}(\eta, \beta) = \sum_{i=0}^{I} \sum_{j=0}^{J} \sum_{k=0}^{K} \eta_{ijk} \cdot x_{ui} \cdot y_{mj} \cdot z_{rk} + \beta \sqrt{V_{CTR}}
\]

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Learning from entity pane log

• Clicks on entity pane
  – Positive feedback from users

• Negative feedback is missing
  – Users didn’t click recommended entities for different reasons

• **Solution**: we use entity pairs as training data instead of individual entities

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Constructing training data

• Assumption
  – Users prefer the related entities they clicked over all the other suggestions

<table>
<thead>
<tr>
<th>User ID</th>
<th>Time</th>
<th>Main entity</th>
<th>Related entity</th>
<th>Rank</th>
<th>Click</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>Man of Steel</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>The Wolverine</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>The Lone Ranger</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>32</td>
<td>7/9/2013 10:32:26</td>
<td>Pacific Rim</td>
<td>World War Z</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>498</td>
<td>6/16/2013 15:16:41</td>
<td>Leonardo DiCaprio</td>
<td>Kate Winslet</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>498</td>
<td>6/16/2013 15:16:41</td>
<td>Leonardo DiCaprio</td>
<td>Baz Luhrmann</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>498</td>
<td>6/16/2013 15:16:41</td>
<td>Leonardo DiCaprio</td>
<td>Johnny Depp</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Likelihood function

• Likelihood function relating $\Psi_{umr}$ values to pairwise preferences:

$$p(r_i > r_j | \Psi_{umr_i}, \Psi_{umr_j}) = \frac{1}{1 + e^{-g_{r_i r_j}(\Psi_{umr_i} - \Psi_{umr_j})}} \quad g_{r_i r_j} \in \{-1, 1\}$$

• Likelihood of all preference observations:

$$p(D|\Psi) = \prod_{(u, m, r_i, r_j) \in D} p(r_i > r_j | \Psi_{umr_i}, \Psi_{umr_j})$$

$$= \prod_{(u, m, r_i, r_j) \in D} \frac{1}{1 + e^{-g_{r_i r_j}(\Psi_{umr_i} - \Psi_{umr_j})}}$$

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Experiments

• Two tasks: 
  - Movie recommendation
  - Celebrity recommendation

• Data (3/2013 ~ 7/2013)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#users</th>
<th>#entities</th>
<th>#instances</th>
</tr>
</thead>
<tbody>
<tr>
<td>Movie</td>
<td>36,641</td>
<td>15,409</td>
<td>224,567</td>
</tr>
<tr>
<td>Celebrity</td>
<td>26,371</td>
<td>2,016</td>
<td>1,450,609</td>
</tr>
</tbody>
</table>

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Features used for movie & celebrity recommendation

<table>
<thead>
<tr>
<th>Movie recommendation</th>
<th>Celebrity recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>User dimension</strong></td>
<td><strong>Main &amp; related movie</strong></td>
</tr>
<tr>
<td>Viewed entities</td>
<td>Actors</td>
</tr>
<tr>
<td>Types of viewed entities</td>
<td>Directors</td>
</tr>
<tr>
<td>Viewed movie's actors</td>
<td>Genres</td>
</tr>
<tr>
<td>Viewed movie's directors</td>
<td>Country of origin</td>
</tr>
<tr>
<td>Viewed movie's genres</td>
<td>Language</td>
</tr>
<tr>
<td>Viewed movie's country</td>
<td>Producers</td>
</tr>
<tr>
<td>Viewed movie's language</td>
<td>Series</td>
</tr>
<tr>
<td>Viewed movie's producers</td>
<td>Story</td>
</tr>
<tr>
<td>Viewed movie's series</td>
<td>Subject</td>
</tr>
<tr>
<td>Viewed movie's story</td>
<td>Music</td>
</tr>
<tr>
<td>Viewed movie's subject</td>
<td>Music</td>
</tr>
<tr>
<td>Viewed movie's music</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed movie's music</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed entities</td>
<td>Viewed pop singers</td>
</tr>
<tr>
<td>Types of viewed entities</td>
<td>Viewed business leaders</td>
</tr>
<tr>
<td>Viewed movie's actors</td>
<td>Viewed writers</td>
</tr>
<tr>
<td>Viewed movie's directors</td>
<td>Viewed musicians</td>
</tr>
<tr>
<td>Viewed movie's genres</td>
<td>Viewed actors</td>
</tr>
<tr>
<td>Viewed movie's country</td>
<td>Viewed film directors</td>
</tr>
<tr>
<td>Viewed movie's language</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed movie's producers</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed movie's series</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed movie's story</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed movie's subject</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed movie's music</td>
<td>.....</td>
</tr>
<tr>
<td>Viewed entities</td>
<td>Profession</td>
</tr>
<tr>
<td>Types of viewed entities</td>
<td>Movie acted</td>
</tr>
<tr>
<td>Attributes of viewed entities</td>
<td>Movie directed</td>
</tr>
<tr>
<td>Viewed pop singers</td>
<td>Book written</td>
</tr>
<tr>
<td>Viewed business leaders</td>
<td>Music genre</td>
</tr>
<tr>
<td>Viewed writers</td>
<td>Organization</td>
</tr>
<tr>
<td>Viewed musicians</td>
<td>Spouse</td>
</tr>
<tr>
<td>Viewed actors</td>
<td>Nationality</td>
</tr>
<tr>
<td>Viewed film directors</td>
<td>Language</td>
</tr>
<tr>
<td>Types</td>
<td>Language</td>
</tr>
<tr>
<td>Types</td>
<td>Types</td>
</tr>
</tbody>
</table>

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Recommendation accuracy

- **Metric:** MRR
  - calculates the reciprocal of the rank of the first hit in the list
  - \[ MRR = \frac{1}{|Q|} \sum_{n=1}^{||Q||} \frac{1}{\text{rank}(n)} \]
Efficacy of personalization

• Case study

A fan of *Leonardo DiCaprio*

<table>
<thead>
<tr>
<th>Related movie entities</th>
<th>Co-click</th>
<th>CTR-model</th>
<th>TEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iron Man 3</td>
<td>Iron Man 3</td>
<td>Django Unchained</td>
<td></td>
</tr>
<tr>
<td>Man of Steel</td>
<td>Star Trek (2013)</td>
<td>Iron Man 3</td>
<td></td>
</tr>
<tr>
<td>Star Trek (2013)</td>
<td>Django Unchained</td>
<td>Man of Steel</td>
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</tr>
</tbody>
</table>

Learning to Recommend Related Entities to Search Users [Bin Bi, et al., WSDM 2015]
Other Entity Personalization Experience
Other Entity Personalization Experience

SIGIR 2015
SIGIR is the major international forum for the presentation of new research results and for the demonstration of new systems and techniques in information retrieval.

Website: SIGIR 2015

Dates: Aug 09 - 13, 2015
Location: Santiago

Submissions due: Jan 28, 2015

People also search for
CIKM 2015 (Oct 19, 2015)
WWW 2015 (May 20, 2015)
AAAI 2016 (Feb 12, 2016)
ECIR 2015 (Mar 29, 2015)
KDD 2015 (Aug 10, 2015)

Special Inspector General for Iraq Reconstruction
The Office of the Special Inspector General for Iraq Reconstruction was created as the successor to the Coalition Provisional Authority Office of Inspector General. SIGIR was an independent government agency created by the Congress to provide oversight of the use of the $52 billion U.S. reconstruction program in Iraq. Stuart W. Bowen, Jr. was appointed Director of the Office.

en.wikipedia.org

Founded: 2004
Other Entity Personalization Experience

\[ P(\text{entity}|\text{user}, \text{query}) \]
Entity Recommendation & Understanding

Taxonomy

• $P(entity|entity)$
  – Recommendations given an entity
    ▫ Co-occurrence
    ▫ Similarity
    ▫ Entity Linking
    ▫ Interpretation

• $P(entity|user)$
  – Recommendations given a user
    ▫ Universal recommender system
    ▫ $P(entity|user, item)$
    ▫ $P(entity|user, query)$

• $P(entity|query)$
  – Recommendations given a query
Entity Recommendation & Understanding

Taxonomy

- \( P(entity|entity) \)
  - Recommendations given an entity
    - Co-occurrence
    - Similarity
    - Entity Linking
    - Interpretation

- \( P(entity|user) \)
  - Recommendations given a user
    - Universal recommender system
    - \( P(entity|user, item) \)
    - \( P(entity|user, query) \)

- \( P(entity|query) \)
  - Recommendations given a query
$P(\text{entity} | \text{query})$

- Entity (“1978 cj5 jeep”)
- Type (“doctors in barcelona”)
- Attribute (“zip code waterville Maine”)
- Relation (“tom cruise katie holmes”)
- Other (“nightlife in Barcelona”)
- Uninterpretable

Ad-hoc Object Retrieval in the Web of Data [Jeffrey Pound, et al., WWW 2010]
\[ P(\text{entity}|\text{query}) \]

- Entity Retrieval/Finding
- Knowledge Base Question and Answering (KB QnA)
- Web-based Question and Answering (Web QnA)
\( P(\text{entity} | \text{query}) \) – Entity Retrieval/Finding
**P(\text{entity}|query)** – Entity Retrieval/Finding

- TREC Entity Track (2009 – 2011)
  - Related Entity Finding Task
  - Given
    - Input entity
    - Type of the target entity (PER/ORG/LOC)
    - Narrative (describing the nature of the relation in free text)
  - Return related entities
$P(\text{entity} | \text{query})$ – Entity Retrieval/Finding

- **Input Entity**: Boeing 747
  - **Target Entity Type**: Organization
  - **Narrative**: Airlines that currently use Boeing 747 planes

- **Input Entity**: The food network
  - **Target Entity Type**: Person
  - **Narrative**: Chefs with a show on the food network

- **Input Entity**: Eurail
  - **Target Entity Type**: Location
  - **Narrative**: What countries does Eurail operate in

- **Input Entity**: Dow Jones
  - **Target Entity Type**: Organization
  - **Narrative**: Find companies that are included in the Dow Jones industrial average
P(entity|query) – Entity Retrieval/Finding

• A typical pipeline

$P(\text{entity} | \text{query})$ – Entity Retrieval/Finding

- Three component model

\[
p(e | E, T, R) \propto p(e | E) \cdot p(T | e) \cdot p(R | E, e)
\]

Related Entity Finding Based on Co-Occurrence [Marc Bron, et al., TREC 2009]
\[ P(\text{entity} | \text{query}) – \text{Entity Retrieval/Finding} \]

\[
P(R|E,e) = P(R|\theta_{Ee}) = \prod_{t \in R} P(t|\theta_{Ee})^{n(t,R)}
\]

\[
P(t|\theta_{Ee}) = \frac{1}{|D_{Ee}|} \sum_{d \in D_{Ee}} P(t|\theta_d)
\]

\[
P(t|\theta_d) = \frac{n(t,d) + \mu \cdot P(t)}{\sum_i' n(t',d) + \mu}
\]

Related Entity Finding Based on Co-Occurrence [Marc Bron, et al., TREC 2009]
\[ P(\text{entity}|\text{query}) \] – Entity Retrieval/Finding

\[ p(e, m = 1|R, S) \propto p(R|e, S) p(e|S) \sum_{t_R} \sum_{t_e} p(m = 1|t_e, t_R) p(t_e|e) p(t_R|R) \]

**Model A**

\[ p(e, m = 1|R) \propto p(R|e) p(e) \sum_{t_R} \sum_{t_e} p(m = 1|t_e, t_R) p(t_e|e) p(t_R|R) \]

**Model B**

## \( P(\text{entity} | \text{query}) \) – Entity Retrieval/Finding

**Input Entity:** Dow Jones  
**Target Entity Type:** Organization

**Narrative:** Find companies that are included in the Dow Jones industrial average

| \( p(m = 1|e, R) \) | \( p(R|e) p(e) \) | MA | \( p(R|e, S) p(e|S) \) | MB |
|---------------------|-----------------|----|----------------------|-----|
| nasdaq              | microsoft       | boeing | coca cola           | boeing         |
| bloomberg           | boeing          | ibm   | boeing               | coca cola      |
| ibm                 | federal reserve | pfizer | cnnmoney             | microsoft      |
| news corporation    | european        | coca cola | futures       | nasdaq        |
| Yahoo               | coca cola       | intel  | microsoft            | ibm            |
| atari               | uav             | alcoa  | pfizer               | intel          |
| washington post     | ibm             | cnnmoney | alcoa            | merck          |
| boeing              | intel           | mcdonald’s | ibm             | dupont         |
| stanford            | futures         | merck  | federal reserve     | caterpillar    |
| enterprise media group | merck     | microsoft | mcdonald’s | stanford       |

**Narrative:** Find companies that are included in the Dow Jones industrial average

$P(\text{entity} | \text{query})$ – Entity Retrieval/Finding

• Knowledge base are largely incomplete

<table>
<thead>
<tr>
<th>Relation</th>
<th>Percentage unknown</th>
<th>All 3M</th>
<th>Top 100K</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROFESSION</td>
<td>68%</td>
<td>24%</td>
<td></td>
</tr>
<tr>
<td>PLACE OF BIRTH</td>
<td>71%</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td>NATIONALITY</td>
<td>75%</td>
<td>21%</td>
<td></td>
</tr>
<tr>
<td>EDUCATION</td>
<td>91%</td>
<td>63%</td>
<td></td>
</tr>
<tr>
<td>SPOUSES</td>
<td>92%</td>
<td>68%</td>
<td></td>
</tr>
<tr>
<td>PARENTS</td>
<td>94%</td>
<td>77%</td>
<td></td>
</tr>
<tr>
<td>CHILDREN</td>
<td>94%</td>
<td>80%</td>
<td></td>
</tr>
<tr>
<td>SIBLINGS</td>
<td>96%</td>
<td>83%</td>
<td></td>
</tr>
<tr>
<td>ETHNICITY</td>
<td>99%</td>
<td>86%</td>
<td></td>
</tr>
</tbody>
</table>

Entity Retrieval/Finding techniques can be used in Knowledge Base Completion

Knowledge Base Completion via Search-Based Question Answering [Robert West, et al., WWW 2014]
$P(\text{entity} | \text{query})$ – Entity Retrieval/Finding
P(entity|query) – Entity Retrieval/Finding

• Challenges
  – The TREC’s related entity finding track is relatively easy since the “query intent” is known
  – In real world search engines, we need to understand the intent of queries

Input Entity: Dow Jones  Target Entity Type: Organization

Narrative: Find companies that are included in the Dow Jones industrial average

Companies in Dow Jones industrial
**P/entity|query** – KB QnA

![Image of search results for "who is Tom Cruise's first wife" and "the tallest building in China"]

**Example:**
- **Query:** "who is Tom Cruise's first wife"
  - **Result:** Mimi Rogers
  - **Data from:** Wikipedia

- **Query:** "the tallest building in China"
  - **Result:** Shanghai Tower
  - **Data from:** Wikipedia
Typical Architect of KB QnA

Open Domain Question and Answering via Semantic Enrichment [Huan Sun, et al., WWW 2015]
An Incomplete List of Academic Papers on KB QnA

### $P(\text{entity} \mid \text{query})$ – KB QnA

- Semantic Parsing

```plaintext
Who did Tom Cruise marry in 1987?

semantic parsing

Type.Person $\sqcap$ Marriage.(Spouse.TomCruise $\sqcap$ StartDate.1987)

execute logical form

Mimi Rogers
```

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
**P(entity|query) – KB QnA**

- Traditional statistical semantic parsing
  - Manually annotated logical forms

  *What's California's capital?*  
  *Capital.California*

  *How long is the Mississippi river?*  
  *RiverLength.Mississippi*

- Limitations
  - Requires experts | slow, expensive, does not scale!
  - Restricted to limited domains

*Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]*
$P(\text{entity}|\text{query})$ – KB QnA

- Simple model suggests candidate logical forms
- Simple model generates canonical utterances
- Ranking of canonical utterances

What languages do people in Brazil use?

What language is the language of Brazil?

Type.HumanLanguage \cap LanguagesSpoken.Brazil

Portuguese, ...

What city is the capital of Brazil?

CapitalOf.Brazil

Advantage: Use a lot of text and paraphrase methods

Paraphrase Model

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
$P(\text{entity} | \text{query})$ – KB QnA

• Input
  – Knowledge-base $K$
  – Training set of question-answer pairs $\{(x_i, y_i)\}_{1}^{n}$
    
    What are the main cities in California? SF, LA, ...

• Output
  – Semantic parser that maps questions $x$ to answers $y$ through logical forms $z$

Countries in Asia $\rightarrow$ Type.Country $\sqcap$ ContainedBy.Asia

$\rightarrow$ China, Japan, India, ...

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
$P(\text{entity}|\text{query})$ – KB QnA

- Logical forms are graph templates

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
$P(\text{entity} \mid \text{query})$ – KB QnA

- Candidate logical forms

What countries in the world speak Arabic?

- ArabicAlphabet
- ArabicLang

  LangSpoken.ArabicLang

  Type.Country \cap LangSpoken.ArabicLang

  Count(Type.Country \cap LangSpoken.ArabicLang)

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
$P(entity|query)$ – KB QnA

- Candidate logical forms

<table>
<thead>
<tr>
<th>Template</th>
<th>Example</th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p.e$</td>
<td>Directed.TopGun</td>
<td>who directed Top Gun</td>
</tr>
<tr>
<td>$p_1.p_2.e$</td>
<td>Employment.EmployerOf.SteveBalmer</td>
<td>Where does Steve Balmer work?</td>
</tr>
<tr>
<td>$p.(p_1.e_1 \sqcap p_2.e_2)$</td>
<td>Character.(Actor.BradPitt\Film.Troy)</td>
<td>Who did Brad Pitt play in Troy?</td>
</tr>
<tr>
<td>$Type.t \sqcap z$</td>
<td>Type.Composer\SpeakerOf.French</td>
<td>What composers spoke French?</td>
</tr>
<tr>
<td>$count(z)$</td>
<td>count(BoatDesigner.NatHerreshoff)</td>
<td>How many ships were designed by Nat Herreshoff?</td>
</tr>
</tbody>
</table>

$p, p_1, p_2$ – Freebase properties  
$e, e_1, e_2$ – Freebase entities  
$t$ – Freebase type  
$z$ – logical form

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
$P(\text{entity}|\text{query})$ – KB QnA

- Canonical utterance generation

Type.Country $\sqcap$ LangSpoken.ArabicLang

- syntactic analysis

What country is Arabic language spoken in?

What country spoken the languages Arabic language?

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
P(entity|query) – KB QnA

• Canonical utterance generation

<table>
<thead>
<tr>
<th>d(p) Categ.</th>
<th>Rule</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>p.e NP</td>
<td>WH d(t) has d(e) as NP?</td>
<td>What election contest has George Bush as winner?</td>
</tr>
<tr>
<td>p.e VP</td>
<td>WH d(t) (AUX) VP d(e)?</td>
<td>What radio station serves area New-York?</td>
</tr>
<tr>
<td>p.e PP</td>
<td>WH d(t) PP d(e)?</td>
<td>What beer from region Argentina?</td>
</tr>
<tr>
<td>p.e NP VP</td>
<td>WH d(t) VP the NP d(e)?</td>
<td>What mass transportation system served the area Berlin?</td>
</tr>
<tr>
<td>R(p).e NP</td>
<td>WH d(t) is the NP of d(e)?</td>
<td>What location is the place of birth of Elvis Presley?</td>
</tr>
<tr>
<td>R(p).e VP</td>
<td>WH d(t) AUX d(e) VP?</td>
<td>What film is Brazil featured in?</td>
</tr>
<tr>
<td>R(p).e PP</td>
<td>WH d(t) d(e) PP?</td>
<td>What destination Spanish steps near travel destination?</td>
</tr>
<tr>
<td>R(p).e NP VP</td>
<td>WH NP is VP by d(e)?</td>
<td>What structure is designed by Herod?</td>
</tr>
</tbody>
</table>

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
\( P(entity|query) \) – KB QnA

- Paraphrase model
  - What countries in the world speak Arabic?
  - What country is Arabic language spoken in?

- Simple paraphrase model utilizing a lot of text
  - Association model - Paralex
  - Vector space model - Wikipedia

\[
\phi_{pr}(x, c) = \phi_{as}(x, c) + \phi_{vs}(x, c)
\]

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
$P(\text{entity} | \text{query})$ – KB QnA

PARALEX corpus with 18 millions pairs of question paraphrases

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
**P(entity|query) – KB QnA**

- Vector Space Model

  *Train word vectors* \( v(w) \):

  \[ v(x) = \frac{1}{|C|} \sum_{x_i \in C} v(x_i) \]

  *Learn a matrix \( W \) to estimate “similarity” score*

  \[ s(x, c) = v(x)^T W v(c) \]

  *Options for \( W \)*

  - Identity: dot product
  - Diagonal: dot product with scaling
  - Full matrix: interactions between dimensions

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
P(entity|query) – KB QnA

\[ x : \text{What type of music did Richard Wagner play?} \]

\[ as : \text{What is the musical genres of Richard Wagner?} \]

\[ vs : \text{What composition has Richard Wagner as lyricist?} \]

\[ x : \text{Where is made Kia car?} \]

\[ as : \text{What place is founded by Kia motors?} \]

\[ vs : \text{What city is Kia motors a headquarters of?} \]

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]
**P(entity|query) – KB QnA**

- WebQuestions dataset
  - What character did Natalie Portman play in Star Wars? ➔ Padme Amidala
  - What kind of money to take to Bahamas? ➔ Bahamian dollar
  - What currency do you use in Costa Rica? ➔ Costa Rican colon
  - What did Obama study in school? ➔ political science
  - What do Michelle Obama do for a living? ➔ writer, lawyer
  - What killed Sammy Davis Jr? ➔ throat cancer

- 5,810 questions crawled from Google Suggest and answered using AMT

*Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]*
$P(\text{entity} | \text{query})$ – KB QnA

Semantic Parsing via Paraphrasing [Jonathan Berant, et al., ACL 2014]

Outperforms previous state-of-the-art
\( P(\text{entity} \mid \text{query}) - \text{KB QnA} \)

- “Who first voiced Meg on Family Guy?”
- \( \lambda x. \exists y. \text{cast}(\text{FamilyGuy}, y) \land \text{actor}(y, x) \land \text{character}(y, \text{MegGriffin}) \)

Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base [Scott Yih, et al., ACL 2015]
**P(entity|query) – KB QnA**

"Who first voiced Meg on Family Guy?"

1. **Topic Entity Linking (E2E tool)**

   ![Diagram](image)

   \[ \phi \rightarrow S_0 \rightarrow S_1 \rightarrow S_2 \]

   - \( S_0 \): \( \phi \)
   - \( S_1 \): Family Guy
   - \( S_2 \): Meg Griffin

2. **Core Inferential Chain (DSSM)**

   ![Diagram](image)

3. **Augmenting Constraints**

   - Leveraging KB more tightly when forming the parse (search pruning)
   - The expressiveness of the query graphs controlled by search actions

Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base [Scott Yih, et al., ACL 2015]
$P(\text{entity} | \text{query})$ – KB QnA

Semantic layer: $\nu$
Semantic projection matrix: $W_2$
Max pooling layer: $\nu$
Max pooling operation
Convolutional layer: $h_i$
Convolution matrix: $W_c$
Word hashing layer: $f_i$
Word hashing matrix: $W_f$
Word sequence: $x_i$

Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base [Scott Yih, et al., ACL 2015]
**P(entity|query) – KB QnA**

### Avg. F1 (Accuracy) on WebQuestions Test Set

<table>
<thead>
<tr>
<th>Method</th>
<th>Avg. F1</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bordes-14a</td>
<td>29.7</td>
<td></td>
</tr>
<tr>
<td>Yao-14</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td>Berant-13</td>
<td>35.7</td>
<td></td>
</tr>
<tr>
<td>Bao-14</td>
<td>37.5</td>
<td></td>
</tr>
<tr>
<td>Bordes-14b</td>
<td>39.2</td>
<td></td>
</tr>
<tr>
<td>Berant-14</td>
<td>39.9</td>
<td></td>
</tr>
<tr>
<td>Yang-14</td>
<td>41.3</td>
<td></td>
</tr>
<tr>
<td>Yih-15</td>
<td>52.5</td>
<td></td>
</tr>
</tbody>
</table>

**Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base [Scott Yih, et al., ACL 2015]**
\(P(\text{entity} | \text{query}) – \text{Web QnA}\)

• Knowledge Base is largely incomplete
\( P(\text{entity}|\text{query}) \) – Web QnA

- Knowledge Base is largely incomplete

<table>
<thead>
<tr>
<th>Relation</th>
<th>Percentage unknown</th>
<th>All 3M</th>
<th>Top 100K</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROFESSION</td>
<td>68%</td>
<td>24%</td>
<td></td>
</tr>
<tr>
<td>PLACE OF BIRTH</td>
<td>71%</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td>NATIONALITY</td>
<td>75%</td>
<td>21%</td>
<td></td>
</tr>
<tr>
<td>EDUCATION</td>
<td>91%</td>
<td>63%</td>
<td></td>
</tr>
<tr>
<td>SPOUSES</td>
<td>92%</td>
<td>68%</td>
<td></td>
</tr>
<tr>
<td>PARENTS</td>
<td>94%</td>
<td>77%</td>
<td></td>
</tr>
<tr>
<td>CHILDREN</td>
<td>94%</td>
<td>80%</td>
<td></td>
</tr>
<tr>
<td>SIBLINGS</td>
<td>96%</td>
<td>83%</td>
<td></td>
</tr>
<tr>
<td>ETHNICITY</td>
<td>99%</td>
<td>86%</td>
<td></td>
</tr>
</tbody>
</table>
$P(\text{entity}|\text{query})$ – Web QnA
An Incomplete List of Academic Papers on Web QnA

• Schlaefer et al. “A pattern learning approach to question answering within the ephyra framework.” TSD-2006.
• Chaturvedi et al. “Joint question clustering and relevance prediction for open domain non-factoid question answering.” WWW-2014
Typical Architect of Web QnA

Who first landed on the Moon?

Apollo 11 was the spaceflight that landed the first humans on the Moon, Americans Neil Armstrong and Buzz Aldrin, on July 20, 1969, at 20:18 UTC.

Open Domain Question and Answering via Semantic Enrichment [Huan Sun, et al., WWW 2015]
\( P(\text{entity} \mid \text{query}) \) – Web QnA

- Detailed Architect
\[ P(\text{entity} | \text{query}) \] – Web QnA

- **QUESTION PROCESSING**
  - Detect question type, answer type
  - Formulate queries to send to a search engine

- **PASSAGE RETRIEVAL**
  - Retrieve ranked documents
  - Break into suitable passages and rerank

- **ANSWER PROCESSING**
  - Extract candidate answers
  - Rank candidates

*Question Answering [Dan Jurafsky, Stanford]*
**$P(\text{entity} | \text{query})$ – Web QnA**

- **Answer Type Detection: Name Entities**
  - Who first landed on the moon?
    - Person
  - Where is the headquarters of Microsoft?
    - Location
  - What is the largest country in terms of population?
    - Country
  - Highest flying bird
    - Animal/Bird

*Question Answering [Dan Jurafsky, Stanford]*
\[ P(\text{entity}|\text{query}) \] – Web QnA

- 6 coarse classes
  - ABBEVIATION, ENTITY, DESCRIPTION, HUMAN, LOCATION, NUMERIC
- 50 finer classes
  - LOCATION: city, country, mountain...
  - HUMAN: group, individual, title, description
  - ENTITY: animal, body, color, currency...

---

Learning Question Classifiers [Xin Li, et al., COLING 2002]
Question Answering [Dan Jurafsky, Stanford]
$P(\text{entity} | \text{query})$ – Web QnA

- Part of the Answer Type Taxonomy

Learning Question Classifiers [Xin Li, et al., COLING 2012]
Question Answering [Dan Jurafsky, Stanford]
**P(entity|query) – Web QnA**

- **Answer Type Detection**
  - Rules
    - Regular expression based rules
      - Who {is|was|are|were} PERSON
    - Question headword
      - Which city in China has the largest number of foreign financial companies?
      - What is the state flower of California?
  - Machine Learning
    - Define a taxonomy of question types
    - Annotate training data for each question type
    - Train classifiers for each question class using a rich set of features: Question words and phrases; Part-of-speech tags; Parse features (headwords); Named Entities; Related words

**Question Answering [Dan Jurafsky, Stanford]**
**$P(\text{entity|query})$ – Web QnA**

- **Passage Retrieval**
  - Retrieve documents using query terms through search engines
  - Segment the documents into shorter units, like paragraphs.

- **Passage ranking, features**
  - Number of Named Entities of the right type in passage
  - Number of query words in passage
  - Number of question N-grams also in passage
  - Proximity of query keywords to passage
  - Longest sequence of question words
  - Rank of the document containing passage
  - ...

---

**Question Answering [Dan Jurafsky, Stanford]**

Run an answer-type named-entity tagger on the passages
  - Each answer type requires a named-entity tagger that detects it
  - If answer type is CITY, tagger has to tag CITY

Return the string with the right type:
  - How many bones in a human body? (Number)
    - The human skeleton is the internal framework of the body. It is composed of **270 bones** at birth – this total decreases to **206 bones** by adulthood after some bones have fused together.

Question Answering [Dan Jurafsky, Stanford]
$P(\text{entity} \mid \text{query})$

**KB QnA**

- **Question**: Who founded apple?
- **Understanding**: KB QnA
- **Knowledge Base**: Apple Inc.
  - **Founder**: Steve Jobs, Ronald Wayne, Steve Wozniak
- **Inventor**: Steve Jobs, Ronald Wayne
- **Product**: iPhone, iPad

**Web QnA**

- **Question**: Who first landed on the Moon?
- **Understanding**: Web QnA
- **Web Corpus**: Apollo 11 was the spaceflight that landed the first humans on the Moon, Americans Neil Armstrong and Buzz Aldrin, on July 20, 1969, at 20:18 UTC.
Open Domain Question and Answering via Semantic Enrichment [Huan Sun, et al., WWW 2015]
\( P(\text{entity}|\text{query}) \) – Web-KB QnA

- Advantages
  - Entity Linking: Reduce redundancy among answer candidates
  - Answer candidates \( \rightarrow \) Freebase types
  - Freebase information \( \rightarrow \) semantic features for ranking

Open Domain Question and Answering via Semantic Enrichment [Huan Sun, et al., WWW 2015]
$P(\text{entity}|\text{query})$ – Web-KB QnA

- Type detection is modeled latently

The likelihood of observing a question $q$ and its answer types $t_a$ as:

$$L = \prod_{i \in D} P(q^i, t^i_a|\alpha, \beta^Q, \beta^T)$$

$$= \prod_{i \in D} \int_{\theta_i} P(\theta_i|\alpha)P(q^i, t^i_a|\theta_i, \beta^Q, \beta^T) \, d\theta_i$$

Variational EM to optimize

$$[\log L] = \sum_{i \in D} E_{Q} \log P(\theta_i|\alpha) + \sum_{i \in D} E_{Q} \log P(Z_i|\theta_i)$$

$$+ \sum_{i \in D} E_{Q} \log P(w \in q^i, t \in t^i_a|Z_i, \beta^Q, \beta^T)$$

$$+ H(Q(\theta, Z))$$

Open Domain Question and Answering via Semantic Enrichment [Huan Sun, et al., WWW 2015]
\( P(\text{entity} | \text{query}) \) – Web-KB QnA

• Experiments
  – Search Queries

<table>
<thead>
<tr>
<th>Systems</th>
<th>MRR</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web QnA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>QuASE</td>
<td>0.6402</td>
<td>0.5962</td>
<td>0.5691</td>
<td>0.5823</td>
</tr>
<tr>
<td>AskMSR+</td>
<td>0.5337</td>
<td>0.3782</td>
<td>0.3760</td>
<td>0.3771</td>
</tr>
<tr>
<td>KB QnA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEMPRE</td>
<td>0.2372</td>
<td>0.2646</td>
<td>0.1940</td>
<td>0.2239</td>
</tr>
</tbody>
</table>

Open Domain Question and Answering via Semantic Enrichment [Huan Sun, et al., WWW 2015]
Outline

• Introduction to Entity and Knowledge
• Demonstration of Microsoft’s Entity Experience
• Entity Recommendation and Understanding
  – $P(\text{entity}|\text{entity})$
  – $P(\text{entity}|\text{user})$
  – $P(\text{entity}|\text{query})$
• Summary
Summary
Entity Recommendation & Understanding

Taxonomy

• $P(\text{entity}|\text{entity})$ - Recommendations given an entity
  – Co-occurrence
  – Similarity
  – Entity Linking
  – Interpretation

• $P(\text{entity}|\text{user})$ - Recommendations given a user
  – Universal Recommender System
  – $P(\text{entity}|\text{user, item})$
  – $P(\text{entity}|\text{user, query})$

• $P(\text{entity}|\text{query})$ - Recommendations given a query
  – Entity Retrieval/Finding
  – Knowledge Base Question and Answering
  – Web Question and Answering
Challenges

• Entity Understanding
  – Ranking, KB completion, Entity Triggering ($P(query|entity)$), …

• User Understanding
  – Users’ Entity Preference, Interest Drift, Multiple Sources (query, url click, entity pane click), …

• Query Understanding
  – Query Intent (definition, list, factoid, question, etc.), Question Type, …

• Document Understanding
  – Entity Linking, NER, Event Detection, …
Challenges

• Query Entity Linking
  – Short and noisy
  – When a user types “Florence”, which one to link?
  – Utilize user location
  – Utilize previous queries in the same session

Personalized Entity Linking System
Challenges

• Question Understanding
  – Rules are not always correct
  – “where is my refund”
    ▫ location?
    ▫ When and how to get refund
  – “when a cat loves a dog”
    ▫ Date Time?
    ▫ TV series
Challenges

- Question and Answering
  - TREC data - Web QnA
  - WebQuestions data – KB QnA
  - All the question in these research datasets are real and valid questions
    - Who first landed on the moon
    - Who killed Abraham Lincoln
  - Real world scenario
    - When is the end of the world
    - Who won the world cup 2017
  - A data set contains both valid and invalid questions
    - Make sure the algorithms won’t return answers for invalid questions
Related Tutorials

• Entity Linking and Retrieval (Meij, Balog and Odijk)

• Entity Resolution (Getoor and Machanavajjhala)

• Constructing and Mining Web-scale Knowledge Graphs tutorial (Bordes, Gabrilovich)

• The Recommender Problem Revisited (Amatriain, Mobasher)

• Question Answering Lecture (Jurafsky)
Thanks!

Hao Ma: haoma at Microsoft.com
Yan Ke: yanke at Microsoft.com