Type Coercion in Watson
Leveraging Community-built Knowledge

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Who is Watson?

- Automatic Open-Domain Question Answering System

  Webby “Person of the Year” 2011
  (www.webbyawards.com)

- Given
  - Rich Natural Language Questions
  - Over a Broad Domain of Knowledge

- Deliver
  - **Precise Answers**: Determine what is being asked & give precise response
  - **Fast Response Time**: Results in few seconds
  - **Accurate Confidences**: Determine likelihood answer is correct
  - **Consumable Justifications**: Explain why the answer is right
The Jeopardy! Challenge

A compelling and notable way to **drive** and **measure** the technology of **automatic Question Answering** along 5 Key Dimensions

- **Broad/Open Domain**
- **Complex Language**
- **High Precision**
- **Accurate Confidence**
- **High Speed**

- **$400**
  Break down "Germany" & get this Sally whom Harry met on film

- **$600**
  A map of Europe on this country's 1997 1,000-lire coin had such errors as depicting Denmark as part of Germany

- **$1000**
  You don't have to pull the feathers off this "chilly" pink sparkling wine originally from Germany
Typing in Jeopardy!

- It's basically a big **kettle** with a close-fitting lid, used to cook pot roasts & stews
- Category: EUROPEAN NATIONALITIES
- Answer: **Dutch Oven**

- Unlucky things happen at Camp Crystal Lake in this 1980 **scarefest**
- Category: MOVIE CALENDAR
- Answer: **Friday the 13th**

- Wanted for general evil-ness; last seen at the Tower of Barad-Dur; it's a **giant eye**, folks. Kinda hard to miss
- Category: LITERARY CHARACTER APB
- Answer: **Sauron**

**The type of thing being asked for is often indicated but can go from specific to very vague.**
Closed Domain Type Checking

• Used in Traditional QA Systems
  
  Based on “Type And Generate” Principle
  • Focus on a pre-determined set of interesting types
    People, Places, Organizations, Dates
  • For these types, run Named Entity Recognizers (NER) over text corpus
    People: {“Einstein”, “Sir I. Newton”..}
    Places: {“Germany”, “UK”..}
    Dates: {“1885”, “3rd April 1715”..}
  • At run-time, given a question, detect lexical answer type (LAT) and:
    Generate candidates from pre-compiled list of LAT instances

Limitations

• Highly brittle – QA system breaks down if type not recognized
• Limited Coverage – need to enumerate all relevant types beforehand
• Dependent on quality of NERs used
Open Domain Type Coercion (TyCor)

• Approach taken in DeepQA
  • Based on “Generate-and-Type” Principle
    • Generate candidates without considering answer type (LAT)
    • Later check whether candidate can be coerced into LAT
  • Use a suite of Type-Coercion Algorithms
  • Use machine-learning to combine information from TyCors

• Advantages
  • More flexible as QA system does not break down if type is not detected or meaningful
  • Much wider type coverage possible using a variety of sources and analytics for TyCor
How TyCor Fits in DeepQA

IN 1698, THIS COMET DISCOVERER TOOK A SHIP CALLED THE PARAMOUR PINK ON THE FIRST PURELY SCIENTIFIC SEA VOYAGE

Keywords: 1698, comet, paramour, pink, ...
AnswerType(comet discoverer)
Date(1698)
Took(discoverer, ship)
Called(ship, Paramour Pink)

Evidence Scoring

Evidence Retrieval

Isaac Newton
Wilhelm Tempel
HMS Paramour
Christiaan Huygens
Halley's Comet
Edmond Halley
Pink Panther
Peter Sellers

Evidence

Related Content (Structured & Unstructured)

Question Analysis

Candidate Answer Generation

Lexical
TyCor
Relations
Temporal

[0.58 0.1 -1.3 ... 0.97]
[0.71 0.9 13.4 ... 0.72]
[0.12 0.0 2.0 ... 0.40]
[0.84 0.8 10.6 ... 0.21]
[0.33 0.0 6.3 ... 0.83]
[0.21 0.9 11.1 ... 0.92]
[0.91 0.0 -8.2 ... 0.61]
[0.91 0.0 -1.7 ... 0.60]

1) Edmond Halley (0.85)
2) Christiaan Huygens (0.20)
3) Peter Sellers (0.05)
**Problem:** Compute type match for candidate w.r.t. LAT
- Both candidate and LAT expressed as **Strings**

- **4 Steps:**
  1. **EDM:** Entity Disambiguation and Matching
  2. **TR:** Type Retrieval
  3. **PDM:** Predicate Disambiguation and Matching
  4. **TA:** Type Alignment

**TyCor Framework**

1. **EDM:** Candidate $\rightarrow$ Instance
   - "JFK" (Cand)
   - Wikipedia:John_F_Kennedy_International (0.7)

2. **TR:** Instance $\rightarrow$ Type
   - "facility" (LAT)
   - Yago:Airport (1.0)

3. **PDM:** LAT $\rightarrow$ Type
   - WN:Facility (0.9)

4. **TA:** Compare LAT-type and Instance-type
   - Helps infer:
     - "Ramadan" is a "month"
     - "Interpreter" is a "job"
     - "Castling" is a "maneuver"
     - "Sauron" is an "eye"
EDM

Fundamental Task in NLP: Map entity string to meaningful reference

Issue 1: Synonymy
Many different ways to refer to the same entity (spellings, aliases, nicknames, abbreviations)

Issue 2: Polysemy
Sense Disambiguation depends on context

Flight took off from JFK...  JFK was assassinated...  Film critics loved JFK...
Using Community-built Knowledge in EDM

For Matching

- Wikipedia redirects (Myanmar => Burma)
- Synonyms / aliases extracted from WP Intro
  - “IBM’s distinctive culture and product branding has given it the nickname Big Blue”
- DBPedia “name” labels (firstName, lastName etc...~100 props)

For Disambiguation

- Wikipedia Disambiguation Pages (wide coverage)
  - ~150K disambiguation pages in 2008
  - E.g. “Java” has >20 Distinct Types
- Measure similarity b/w sense text and entity context (using BOW, LSA etc)

Output: Ranked list of entity resources (Wikipedia URIs)

- Ranking based on: Source, Popularity, Similarity

Results

- Evaluation on Wikipedia: Precision: 75%, Recall: 95% (state-of-the-art)
Type Retrieval (TR)

- Obtain Types for Instances
- Sample Taxonomies Used In DeepQA:
  - WordNet
  - Wikipedia Lists
  - Wikipedia Categories
  - Yago Ontology (from DBpedia)
  - Auto-Mined Types from Text (Wikipedia Intro)

<table>
<thead>
<tr>
<th>RECALL</th>
<th>PRECISION</th>
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</thead>
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- Interesting Points
  - Type Systems are linked
    - Yago → WordNet
  - Wiki-Categories and Lists contain extra information (modifiers)
    - Einstein: German-Inventor, Swiss-Vegetarian, Patent-Examiner
    - List of “German Cities”
  - Automatically Mined Types reflect real world usage
    - Fluid -is-a- Liquid (strictly speaking incorrect)
PDM

• Predicate (LAT) Disambiguation and Matching
  – LAT: star

In the northern hemisphere, latitude is equal to the angle above the horizon of this star, Alpha Ursae Minoris

This star of "The Practice" played Clint Eastwood's Secret Service partner in the film "In the Line of Fire"

• Similar in principle to EDM
  – EDM – map named entity → instance
  – PDM – map generic noun → class/type

• LATTE in DeepQA:
  – Map LAT to WordNet Concept(s): Order based on sense ranks
  – Pull in LAT Types that are statistically related in DBpedia
    – “Brand” → “Product” (0.83)
Type Alignment

- Type Matching Problem
  - Compare candidate types with LAT types
  - Produce a score depending degree of Match

- Various Types of Match Considered

```
Candidate-Type: Airport
LAT-Type: Air Field

LAT-Type: TrainStation

Subclass Match (1.0)
Sibling Match (0.5)
Deep LCA Match (0.25)
Disjoint Types (-1.0)
```
Putting it all together

• TyCor Score = EDM * TR * PDM * TA

• Intermediate Failure
  - If any step fails, TyCor Score = 0 (consider smoothing)
  - Expose which step failed to final model (EDM-Failure, PDM-Failure…)

• An-TyCor
  - When TA score is -1 (Disjoint Types) → AnTyCor Feature added to model
  - Strong negative signal against candidate
  - Helps rules out candidates of wrong type (e.g. LAT: Country, Candidate: Einstein)

• Multiple LATs
  - When multiple LATs in question with confidences: (L1, L2..Ln)
  - Final TyCor Score (weighted-sum) = (L1 * Tyc1) + (L2 * Tyc2) + .. (Ln * Tycn)

• TyCor Algorithm Suite in DeepQA
  - 14 TyCors Developed (3 that use Wikipedia and DBpedia)
  - All TyCors follow 4 key steps
  - Each TyCor score is a separate feature in model
  - Model learns weights on diff. TyCors: balances/combines type information
Evaluating TyCors on Ground Truth

Benchmark creation:
- Annotated Top 10 Candidates for 1615 Jeopardy! Questions
  - Judgement: Does candidate match LAT – Y/N?
- Total <LAT, Candidate> Pairs for Testing: 25,991 (due to multiple LATs)
Evaluating TyCors on end-to-end QA

• Two Watson Configurations:
  1. **Watson-LITE**: Cand. Gen + Merging + Ranking (NO Answer Scoring)
  2. **Watson-FULL**: LITE + All Answer Scoring

- All gains over “No TyCor” are statistically significant
- Combining all 3 TyCors better than any one (Net gain: 5-6%)
Overall TyCor Impact
(Experiment done in Nov 2011)
Summary

**THEORY**

- TyCor Framework provides flexible, robust answer typing
  - Core Idea: Treat type-match as *just another answer scoring feature*
  - Conceptual Separation of Steps: EDM, Type Retrieval, PDM, Type Alignment
  - Each step produces score reflecting uncertainty of mapping
  - Scores are features in ML model (with special features for failures)

**IMPLEMENTATION**

- Community-built Knowledge useful in TyCor
  - Scrape information from *Wikipedia*
    - Lists, Categories, Redirects, Anchor-Links, Intro-text
  - Map to *DBPedia*
    - Utilize Alternate names, Type Information, Links to YAGO / WN
  - Extend *YAGO* with Disjoints

**APPLICATION**

- TyCor has significant impact in open-domain QA
  - …and Watson won the Jeopardy! challenge
- Beyond Jeopardy!: Watson MD
  - Leverage UML-S and other Medical Ontologies in TyCor
BACKUP
Toronto vs. Chicago

**US CITIES**

Its largest airport is named for a World War II hero; its second largest, for a World War II battle.

Overall confidence was below threshold for both answers.

<table>
<thead>
<tr>
<th>City</th>
<th>Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toronto</td>
<td>14%</td>
</tr>
<tr>
<td>Chicago</td>
<td>11%</td>
</tr>
<tr>
<td>Omaha</td>
<td>10%</td>
</tr>
</tbody>
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Low because of weak evidence in content.

Low because being a **US City** is not a strong requirement simply based on Jeopardy! category.
Our Focus is on reusable NLP technology for analyzing vast volumes of *as-is* text. Structured sources (DBs and KBs) provide background knowledge for interpreting the text.

We do NOT attempt to anticipate all questions and build databases.

We do NOT try to build a formal model of the world.

In a random sample of 20,000 questions we found 2,500 distinct types*. The most frequent occurring <3% of the time. The distribution has a very long tail.

And for each these types 1000’s of different things may be asked.

Even going for the head of the tail will barely make a dent.

*13% are non-distinct (e.g., it, this, these or NA)
Acquiring Structured Data in Watson

• Obtain web-based (semi) structured resources
  – E.g. DBpedia, Yago, Wikipedia Categories, Redirects, Lists

• Process Raw Structured Data:

  • **Filter Noise**
    • Discard noisy Wikipedia Redirects
      • e.g. *Eliza Doolittle* (character) -> *Pygmalion* (play)

  • **Normalize Data**
    • Standardize temporal expressions
      • “20\text{th} Jan 1950” -> “01-20-1950”, “13\text{th} Century” -> “XX-XX-12XX”
    • Normalize relation names
      • \{georss\#lat, #latitude #geo-lat\} - Latitude

  • **Extend Ontologies**
    • Add disjoints – e.g. *Disjoint(Country, Person)* - Useful to rule out candidates with incompatible answer type
Watson’s Buzz

As soon as the clue is read an **enable signal** does 3 things simultaneously
- Activates the hand-held buzzers
- Illuminates a visible light strip
- Signals Watson

**Equal Footing:** Both Humans and Watson
- Learn about the enable at the same time
- Have to physically push down identical buzzers

**Advantage Humans**
By listening and anticipating the enable signal, humans can buzz in <5 ms
Watson is not hearing the host and cannot anticipate the enable signal

**Advantage Watson**
Watson, although not the fastest, is consistently fast
Assuming Watson can compute an answer and confidence in time (not always quick enough)
Watson does not risk the ¼ sec pre-buzz penalty – waits for enable

Watson uses a confidence-weighted buzzer scheme and will hesitate on less confidence answers to avoid “tipping and losing” to better players
Overall TyCor Impact
(Experiment done in Aug 2009)

An ensemble of TyCor components

+ ~10%