Question Answering

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(some of these slides were adapted from Giuseppe Attardi, Girish K)

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- Natural language processing techniques for QA
  - Word embedding

Question Answering

- Earlier IR systems focus on queries with short keywords
  - Most of search engine queries are short queries.
- QA systems focus in natural language question answering.
- Outline
  - What is QA
  - Examples of QA systems/algorithms.

People *want* to ask questions…

Examples from Ask.com query log

how much should i weigh
what does my name mean
how to get pregnant
where can i find pictures of hairstyles
who is the richest man in the world
what is the meaning of life
why is the sky blue
what is the difference between white eggs and brown eggs
can you drink milk after the expiration date
what is true love
what is the jonas brothers address

Around 10-20% of query logs

General Search Engine

- Include question words etc. in stop-list with standard IR
- Sometime it works. Sometime it requires users to do more investigation (a study in 2008)
  - Question: *Who was the prime minister of Australia during the Great Depression?*
    - Answer: *James Scullin (Labor) 1929–31.*
    - *Ask.com gives an explicit answer.*
    - *Google's top 1-2 results are also good.*
  - *what is phone number for united airlines*
    - *Ask.com gives a direct answer*
    - *Google gives no direct answers in top 10.*
  - *How much money did IBM spend on advertising in 2006?*
    - No engine can answer

Why QA?

- QA engines attempt to let you ask your question the way you'd normally ask it .
  - More specific than short keyword queries
    - Orange chicken
    - what is orange chicken
    - how to make orange chicken
  - Inexperienced search users

- What is involved in QA?
  - Natural Language Processing
    - Question type analysis and answer patterns
    - Semantic Processing
    - Syntactic Processing and Parsing
  - Knowledge Base to store candidate answers
  - Candidate answer search and answer processing

AskJeeves (now Ask.com)

- **Eariler AskJeeves** is probably most well-known QA site
  - It largely does pattern matching to match your question to their own knowledge base of questions
  - Has own knowledge base and uses partners to answer questions
  - Catalogues previous questions
  - Answer processing engine
    - Question template response
  - If that works, you get template-driven answers to that known question
  - If that fails, it falls back to regular web search
- **Ask.com:**
  - Search answers from a large web database
  - Deep integration with structured answers

Question Answering at TREC

- Question answering competition at TREC consists of answering a set of 500 fact-based questions, e.g., "*When was Mozart born*?".
- For the first three years systems were allowed to return 5 ranked answer snippets (50/250 bytes) to each question.
  - IR think
  - Mean Reciprocal Rank (MRR) scoring:
    - 1, 0.5, 0.33, 0.25, 0.2, 0 for 1, 2, 3, 4, 5, 6+ doc
  - Mainly Named Entity answers (person, place, date, …)
- From 2002 the systems were only allowed to return a single *exact* answer and the notion of confidence has been introduced.

The TREC Document Collection

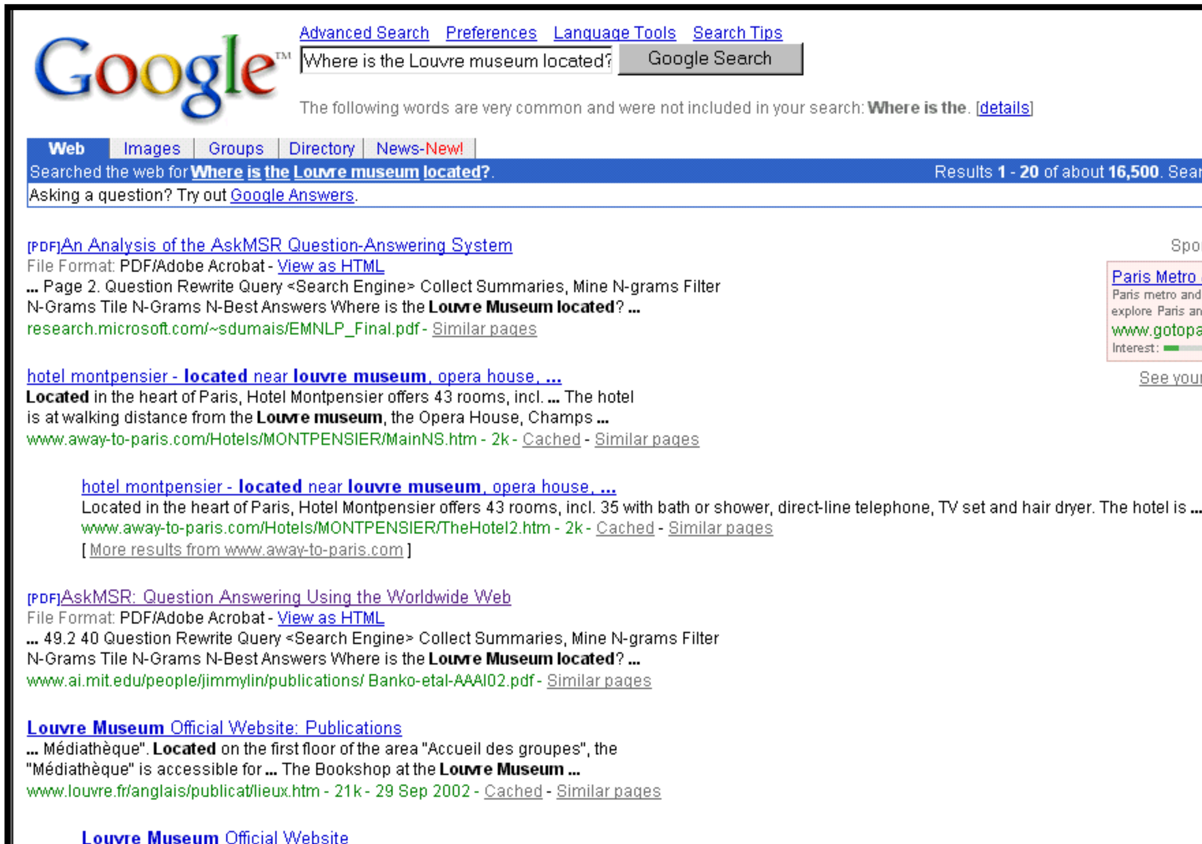
- The current collection uses news articles from the following sources:
    - AP newswire,
    - New York Times newswire,
    - Xinhua News Agency newswire,
- In total there are 1,033,461 documents in the collection. 3GB of text
- Clearly this is too much text to process entirely using advanced NLP techniques so the systems usually consist of an initial information retrieval phase followed by more advanced processing.
- Many supplement this text with use of the web, and other knowledge bases

Sample TREC questions

1. Who is the author of the book, "The Iron Lady: A Biography of Margaret Thatcher"?
2. What was the monetary value of the Nobel Peace Prize in 1989?
3. What does the Peugeot company manufacture?
4. How much did Mercury spend on advertising in 1993?
5. What is the name of the managing director of Apricot Computer?
6. Why did David Koresh ask the FBI for a word processor?
7. What debts did Qintex group leave?
8. What is the name of the rare neurological disease with symptoms such as: involuntary movements (tics), swearing, and incoherent vocalizations (grunts, shouts, etc.)?

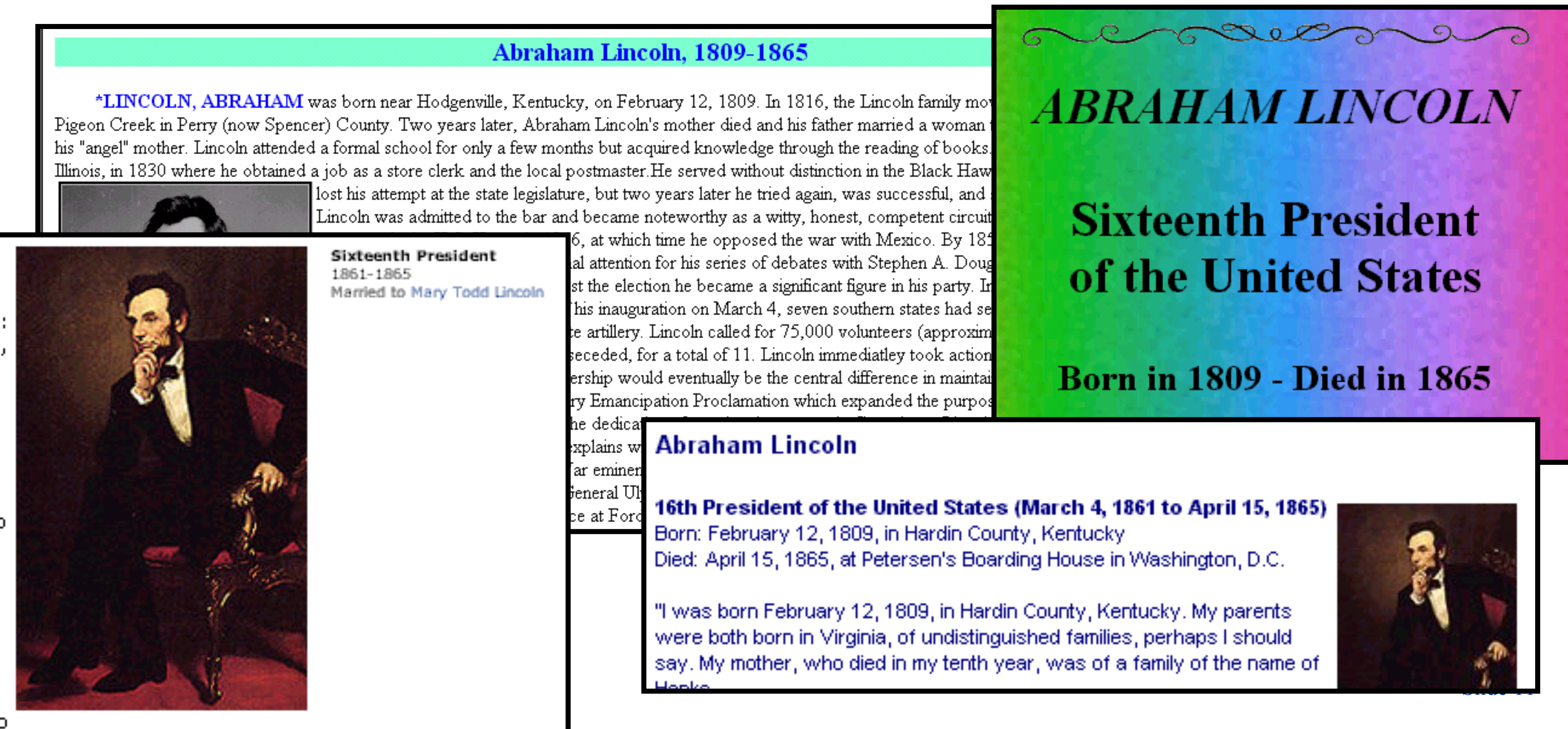
AskMSR

- ***Web Question Answering: Is More Always Better?***
  - Dumais, Banko, Brill, Lin, Ng, SIGIR 2002
- **Q: "Where is the Louvre located?"**
- Want "Paris" or "France" or "75058 Paris Cedex 01" or a map
- <u>Don't</u> just want URLs

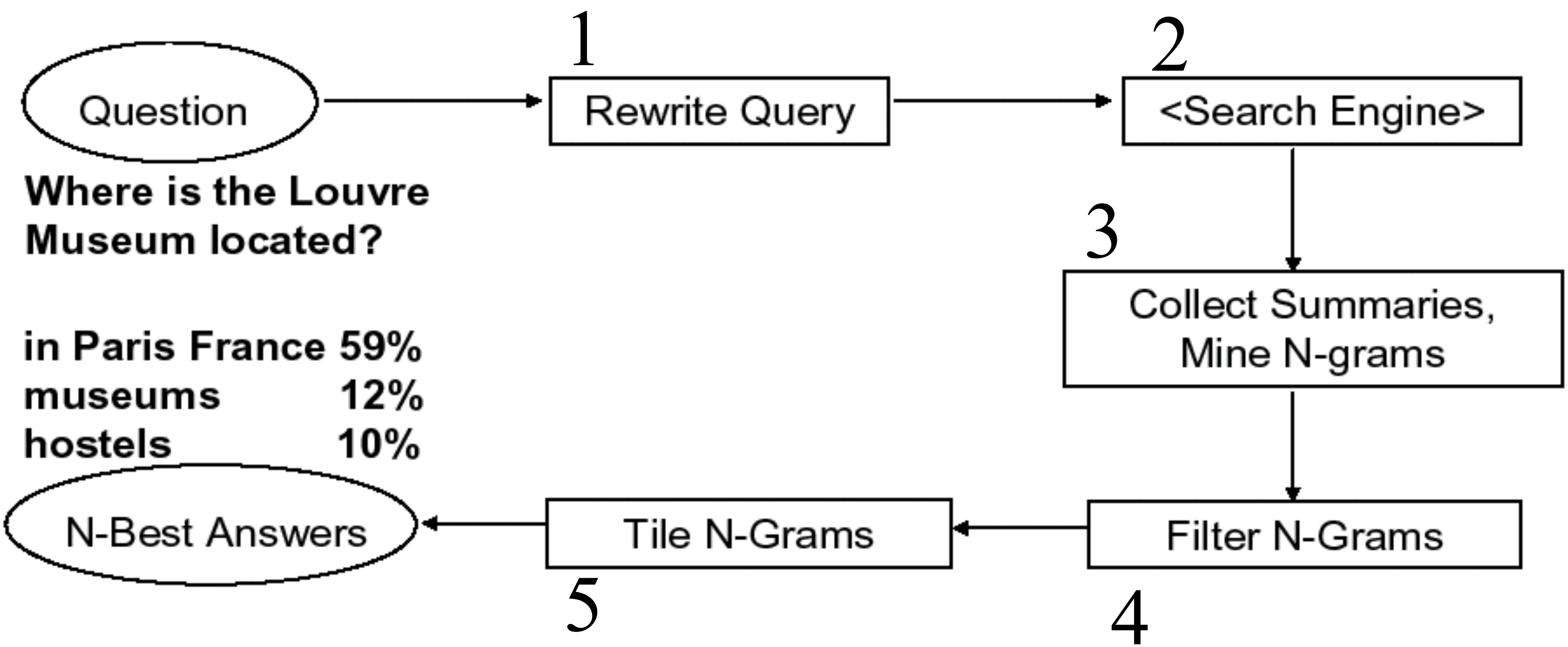


AskMSR: Shallow approach

- *In what year did Abraham Lincoln die?*
- Ignore hard documents and find easy ones



AskMSR: Details



Step 1: Rewrite queries

- Intuition: The user's question is often syntactically quite close to sentences that contain the answer
  - Where is the Louvre Museum located?
  - The Louvre Museum is located in ***Paris***
  - Who created the character of Scrooge?
  - ***Charles Dickens*** created the character of Scrooge.

Query rewriting

- Classify question into seven categories
  - **Who** is/was/are/were…?
  - **When** is/did/will/are/were …?
  - **Where** is/are/were …?

a. Category-specific transformation rules

eg “For Where questions, move ‘is’ to all possible locations”

“Where is the Louvre Museum located”

→ “is the Louvre Museum located”

→ “the is Louvre Museum located”

→ “the Louvre is Museum located”

→ “the Louvre Museum is located”

→ “the Louvre Museum located is”

Nonsense, but who cares? It’s only a few more queries to Google.

b. Expected answer “Datatype” (eg, Date, Person, Location, …)

When was the French Revolution? → DATE

- Hand-crafted classification/rewrite/datatype rules (Could they be automatically learned?)

Query Rewriting - weights

- One wrinkle: Some query rewrites are more reliable than others

Where is the Louvre Museum located?

Weight 1
Lots of non-answers could come back too

Weight 5
if we get a match,
it's probably right

+"the Louvre Museum is located"

+Louvre +Museum +located

Step 2 and Step 3

- Step 2: Query Search engine
  - Send all rewrites to a Web search engine
  - Retrieve top N answers (100?)
  - For speed, rely just on search engine's "snippets", not the full text of the actual document

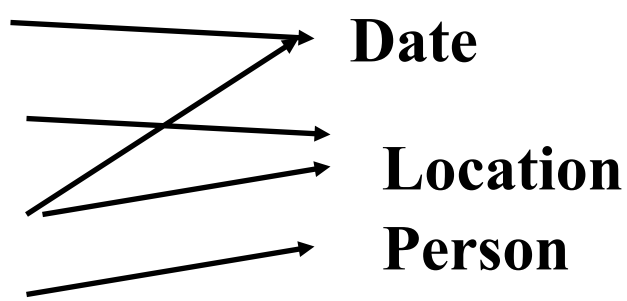
- Step 3: Mining N-grams
  - Unigram, bigram, trigram, … N-gram:
    list of N adjacent terms in a sequence
  - Eg, "Web Question Answering: Is More Always Better"
    - Unigrams: Web, Question, Answering, Is, More, Always, Better
    - Bigrams: Web Question, Question Answering, Answering Is, Is More, More Always, Always Better
    - Trigrams: Web Question Answering, Question Answering Is, Answering Is More, Is More Always, More Always Betters

Mining N-Grams

- Simple: Enumerate all N-grams (N=1,2,3 say) in all retrieved snippets
    - Use hash table and other fancy footwork to make this efficient
- Weight of an n-gram: occurrence count, each weighted by "reliability" (weight) of rewrite that fetched the document
- Example: "Who created the character of Scrooge?"
  – Dickens - 117
  – Christmas Carol - 78
  – Charles Dickens - 75
  – Disney - 72
  – Carl Banks - 54
  – A Christmas - 41
  – Christmas Carol - 45
  – Uncle - 31

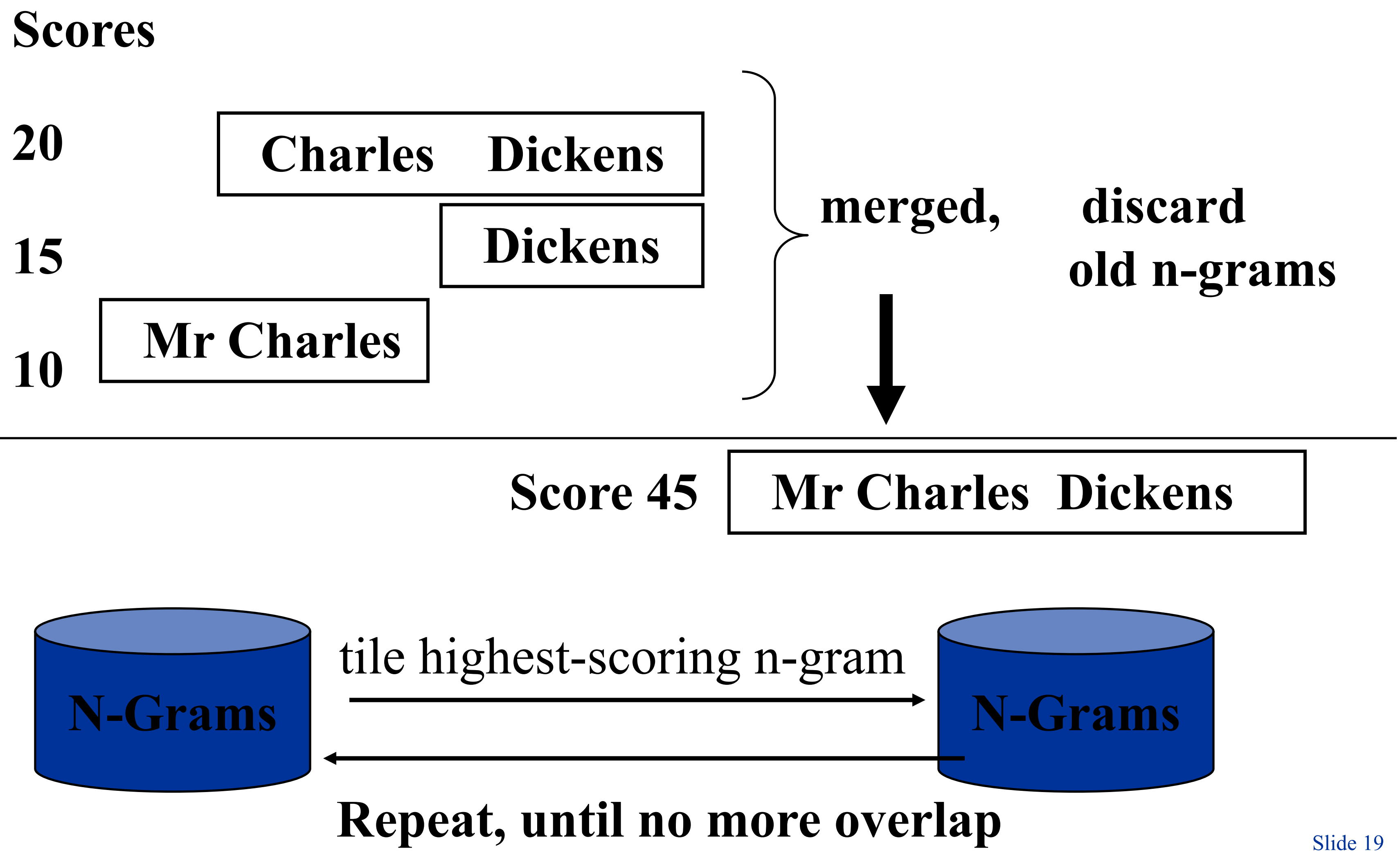
Step 4: Filtering N-Grams

- Each question type is associated with one or more “**data-type filters**” = regular expression
- When…
- Where…
- What …
- Who …



- Boost score of n-grams that do match regexp
- Lower score of n-grams that don’t match regexp

Step 5: Tiling the Answers



Results

- Standard TREC contest test-bed:
  ~1M documents; 900 questions
- Technique doesn't do too well (though would have placed in top 9 of ~30 participants!)
  - MRR = 0.262 (ie, right answered ranked about #4-#5)
- Using the Web as a whole, not just TREC's 1M documents… MRR = 0.42 (ie, on average, right answer is ranked about #2-#3)
  - Why? Because it relies on the enormity of the Web!

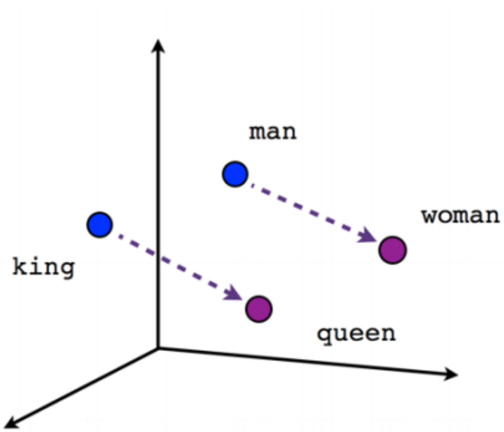
NLP with Word Embedding Techniques

- Deep Learning for NLP by Richard Socher (http://cs224d.stanford.edu/)
- Mikolov, Tomas; Sutskever, Ilya; Chen, Kai; Corrado, Greg S.; Dean, Jeff (2013). *Distributed representations of words and phrases and their compositionality*. Advances in Neural Information Processing Systems. arXiv:1310.4546.
- Tutorial and Visualization tool by Xin Rong (http://www-personal.umich.edu/~ronxin/pdf/w2vexp.pdf)
- Word2vec in Gensim by Radim Řehůřek (http://rare-technologies.com/deep-learning-with-word2vec-and-gensim/)

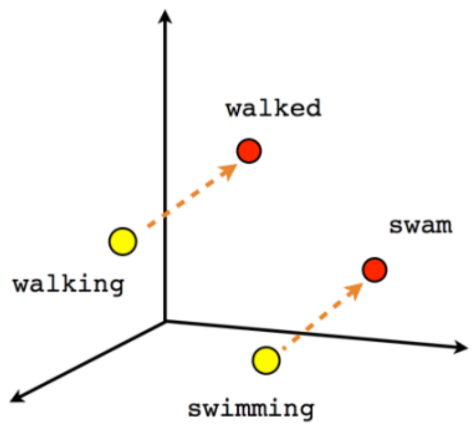
Word Representations

Traditional Method - Bag of Words Model	Word Embeddings
• Uses one hot encoding • Each word in the vocabulary is represented by one bit position in a HUGE vector. • For example, if we have a vocabulary of 10000 words, and "Hello" is the 4th word in the dictionary, it would be represented by: 0 0 0 1 0 0 . . . . 0 0 0 0 • Context information is not utilized	• Stores each word in as a point in space, where it is represented by a vector of fixed number of dimensions (generally 300) • Unsupervised, built just by reading huge corpus • For example, "Hello" might be represented as : [0.4, -0.11, 0.55, 0.3 . . . 0.1, 0.02] • Dimensions are basically projections along different axes, more of a mathematical concept.

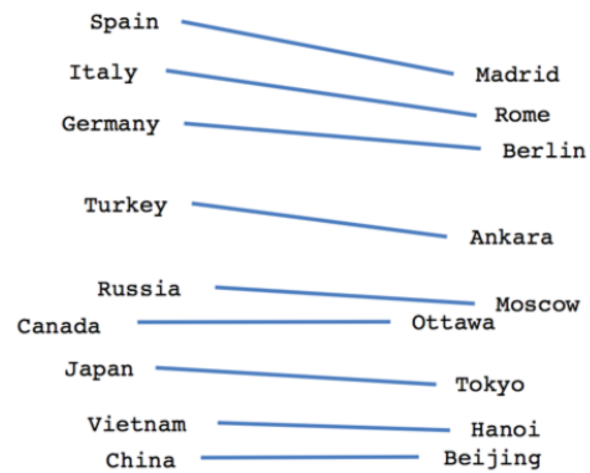
Examples



Male-Female



Verb tense



Country-Capital

vector[Queen] = vector[King] - vector[Man] + vector[Woman]

The Power of Word Vectors

- They provide a fresh perspective to ***ALL*** problems in NLP, and not just solve one problem.

- Technological Improvement
  - Rise of deep learning since 2006 (Big Data + GPUs + Work done by Andrew Ng, Yoshua Bengio, Yann Lecun and Geoff Hinton)
  - Application of Deep Learning to NLP – led by Yoshua Bengio, Christopher Manning, Richard Socher, Tomas Mikalov

- The need for unsupervised learning . (Supervised learning tends to be excessively dependant on hand-labelled data and often does not scale)

Applications of Word Vectors

1. Word Similarity

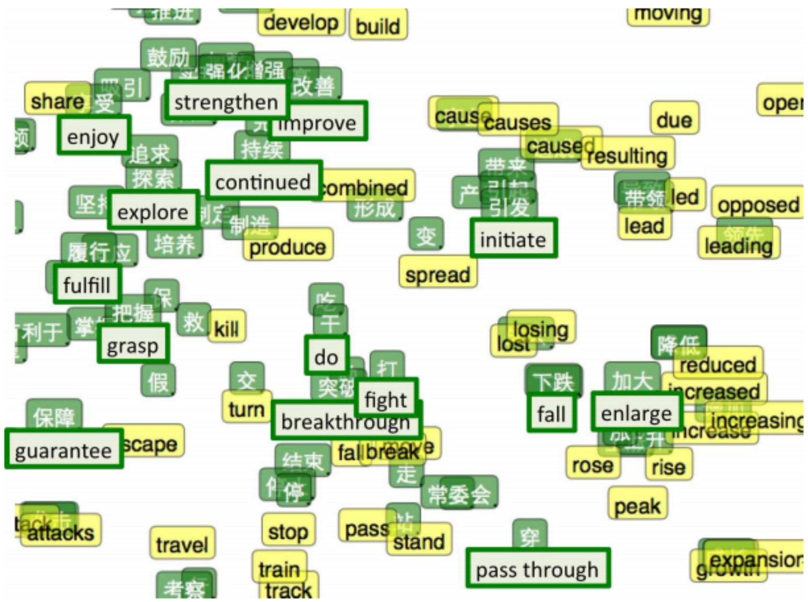
Classic Methods : Edit Distance, WordNet, Porter's Stemmer, Lemmatization using dictionaries

- Easily identifies similar words and synonyms since they occur in similar contexts
- Stemming (thought -> think)
- Inflections, Tense forms
- *eg. Think, thought, ponder, pondering,*
- *eg. Plane, Aircraft, Flight*

Applications of Word Vectors

2. Machine Translation

Classic Methods： Rule-based machine translation, morphological transformation



Applications of Word Vectors

3. Part-of-Speech and Named Entity Recognition

Classic Methods : Sequential Models (MEMM , Conditional Random Fields), Logistic Regression

	POS WSJ (acc.)	NER CoNLL (F1)
State-of-the-art*	97.24	89.31
Supervised NN	**96.37**	**81.47**
Unsupervised pre-training followed by supervised NN**	**97.20**	**88.87**
+ hand-crafted features***	97.29	89.59

Noun	*book/books, nature,*
Verb	*eat, wrote*
Auxiliary	*can, should, have*
Adjective	*new, newer, newest*
Adverb	*well, urgently*
Numbers	*872, two, first*
Article/Determiner	*the, some*
Conjunction	*and, or*
Pronoun	*he, my*
Preposition	*to, in*
Particle	*off, up*
Interjection	*Ow, Eh*

Applications of Word Vectors

4. Relation Extraction

Classic Methods : OpenIE, Linear programing models, Bootstrapping

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

Applications of Word Vectors

5. Sentiment Analysis

Classic Methods : Naive Bayes, Random Forests/SVM

- Classifying sentences as positive and negative
- Building sentiment lexicons using seed sentiment sets
- No need for classifiers, we can just use cosine distances to compare unseen reviews to known reviews.

```
Enter word or sentence (EXIT to break): sad

Word: sad  Position in vocabulary: 4067

                                              Word       Cosine distance
------------------------------------------------------------------------
                                         saddening              0.727309
                                               Sad              0.661083
                                          saddened              0.660439
                                      heartbreaking             0.657351
                                      disheartening             0.650732
                                      Meny_Friedman             0.648706
                            parishioner_Pat_Patello             0.647586
                                         saddens_me             0.640712
                                        distressing             0.639909
                                  reminders_bobbing             0.635772
                                   Turkoman_Shiites             0.635577
                                            saddest             0.634551
                                        unfortunate             0.627209
                                              sorry             0.619405
                                        bittersweet             0.617521
                                             tragic             0.611279
                                         regretful              0.603472
```

Applications of Word Vectors

6. Clustering

- Words in the same class naturally occur in similar contexts, and this feature vector can directly be used with any conventional clustering algorithms (K-Means, agglomerative, etc). Human doesn't have to waste time hand-picking useful word features to cluster on.

7. Question answering.

Aliaksei Severyn and Alessandro Moschitti. *Learning to Rank Short Text Pairs with Convolutional Deep Neural Networks*. SIGIR, 2015