What Will Search Engines be Changed by NLP Advancements

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ICTIR-2018, Tianjin
Introduction

• Intelligence and naturalness are two driving forces of a search engine

• Intelligence
  Precisely understanding user’s intent and finding out accurate answers

• Naturalness
  Expressing user’s intent and presenting the search results in a natural way

• NLP has been vital (though at shallow level) to both intelligence and naturalness

• With new advancements of NLP, what new changes will be brought to search?
Search engine architecture (Bing)

**Online**
- **Pre-Web Phase**
  - Context & Query Understanding
- **Web Phase**
  - Ten Blue Links
  - Superfresh
  - Instant Answer/Chat
  - Task & Social Pane
  - Advertisement
- **Post-Web Phase**
  - Whole Page Ranking & Suppression
- **UX**

**Offline (Crawler)**
- **Multi-Media Data**
  - MM Pages
- **Unstructured Data**
  - Web Pages
  - Superfresh Discovery
- **Structured Data**
  - Satori/Freebase
- **Semi-Structured Data**
  - LinkedIn
  - Yelp
  - TripAdvisor
NLP in search engine

Search Result Page

Post-Web Phase
- Whole Page Ranking
- Suppression
- Coherence
- Ranking Model
- Query Suggestion

Web Phase

Ten Bleu Links
- Bag-of-word model
- Translation model
- Click-through
- Summarization/snippet
- ...

Instant Answer/Chat
- Knowledge-based QA
- Visual/Video QA
- MRC
- Task-oriented bot
- ...

Task & Social Pane
- Knowledge graph
- Entity linking
- Social networks
- User profiling
- ...

Super Fresh
- News recommendation
- Personalized news feed
- Event detection
- News classification
- ...

Advertisement
- User intent detection
- Slot tagging
- Query-Ads matching
- Ads keyword generation
- ...

Pre-Web Phase

Word Breaking
Spelling
Synonym
Dependency Parsing
Entity Linking
Intent Classification
Semantic Parsing
Word/Sentence Embedding
User Profiling
Query Rewriting
In the following, I try to answer

- What are new advancements of NLP?
- What new changes will be brought to search?
NLP technologies

NLP fundamental
- Word embedding
- Word breaker, LM
- Syntactic-semantic analysis
- Discourse analysis

NLP core tech
- MT
- QA, QU and QG
- IR
- IE

Dialogue
- Knowledge engineering
- Language generation
- Recommendation system

NLP+
- Search engine
- Customer service
- Business intelligence
- Spoken assistant

User modelling
Big data
Computing power
ML
KB/common sense

ML
Big data
Computing power
ML
KB/common sense
NLP innovations in MS
DNN techs that changed NLP

DNN

Embedding

Attention

RNN/LSTM/GRU

Encoder-Decoder

Reinforcement learning
Recent breakthroughs in MSRA

2017

23 CPS
Chatbot

Xiaoice

2018

82.65%
Machine Reading

SQuAD

2018

69%
Machine Translation

WMT-2017

2018

61.34%
Grammar check

CoNLL-2014
CoNLL-10
JFLEG
Important trends

- QA
- Multi-lingual
- Multi-modal
- MRC
- Personalized recommendation
Important trends

- QA
- Multi-lingual
- Multi-modal
- MRC
- Personalized recommendation
Question-Answering

Diagram showing the flow of question-answering processes involving CommunityQA, KBQA, TableQA, PassageQA, VQA, and Human-in-the-Loop (HI) components. The processes involve knowledge, tables, documents, and images, with automatic responses for each type.
KBQA approaches

Semantic Parsing-based KBQA

**Query:** where was Barack Obama born?

**Logical Form:** \( \lambda x. \text{Place_of_Birth}(\text{Barack Obama}, x) \)

Answer Look up from KB

\(<\text{Barack Obama, Place_of_Birth, Honolulu}>\)

Answer Ranking-based KBQA

**Query:** where was Barack Obama born?

**Answer Representation:**
- Feature
- NLG
- Sub-graph
- Embedding

\(<\text{Barack Obama, Place_of_Birth, Honolulu}>\)
Ranking with NL description of the candidate answers

(Berant and Liang, 2014)

Ranking Model

(question-generated question)

When is the date of birth of Barack Obama?

Pattern-based Question Generation

DataOfBirth.BarackObama

…

What city is the place of birth of Barack Obama?

Pattern-based Question Generation

Type.City ∩ PlaceOfBirth.BarackObama

Predicate POS | Question Generation Pattern
---|---
NP | What TYPE is the NP of ENTITY?
NP VP | What NP is VP by ENTITY?
… | …

Ranking Model

- Compute similarity between input question and each generated question
- Features
  - Association Model (paraphrasing)
  - Vector Space Model (word embedding)
Ranking with embedding of candidate answers

(Bordes et al., 2014)

Who did Clooney marry in 1987?
Combinatorial Categorial Grammar (CCG)

- CCG captures **syntactic** and **semantic** information jointly

A CCG Rule Example

\[
\text{border} := (S\NP)/\NP \quad \lambda x\lambda y. \text{Border}(x, y)
\]

- Match natural language input
- Syntactic symbols: S, N, NP, ADJ and PP
- Syntactic combinator: / and \ which specify combination orders and directions

- λ-Calculus expression
CCG-based semantic parsing for KBQA
(Zettlemoyer and Collins, 2007; Kwiatkowski et al., 2011)

State \[\lambda x. \text{Type}(\text{State}, x)\] \hspace{1cm} \text{borders} \hspace{1cm} \text{New Mexico} \\
\[
\begin{align*}
\text{NP} & \\
\text{(S\text{\textbackslash NP})/NP} & \hspace{1cm} \lambda x \lambda y. \text{Border}(x, y) & \text{NP} \\
\text{NP} & \hspace{1cm} \text{New Mexico} \\
\text{S\text{\textbackslash NP}} & \hspace{1cm} \lambda x. \text{Border}(x, \text{New Mexico}) \\
\text{S} & \lambda x. \text{Type}(\text{State}, x) \land \text{Border}(x, \text{New Mexico})
\end{align*}
\]
Semantic parsing with encoder-decoder
(Dong and Lapata, 2018)
Semantic parsing with multi-gates and syntax constraints
MSRA-NLC @ ACL 2018

Decoder

Encoder

Attention

How many CFL teams are from York College?

Table

<table>
<thead>
<tr>
<th>Pick #</th>
<th>CFL Team</th>
<th>Player</th>
<th>Position</th>
<th>College</th>
</tr>
</thead>
<tbody>
<tr>
<td>27</td>
<td>Hamilton Tiger-Cats</td>
<td>Connor Healy</td>
<td>DB</td>
<td>Wilfrid Laurier</td>
</tr>
<tr>
<td>28</td>
<td>Calgary Stampeders</td>
<td>Anthony Forgone</td>
<td>OL</td>
<td>York</td>
</tr>
<tr>
<td>29</td>
<td>Toronto Argonauts</td>
<td>Frank Hoffman</td>
<td>DL</td>
<td>York</td>
</tr>
</tbody>
</table>

SQL

```
SELECT COUNT(CFL Team) WHERE College = "York"
```

Output

```
t = 0
<SQL>
SELECT column, WHERE COUNT value, MIN, MAX, AND >, <, =

Decoder

Encoder

Attention

Pick # CFL Team Player Position College
27 Hamilton Tiger-Cats Connor Healy DB Wilfrid Laurier
28 Calgary Stampeders Anthony Forgone OL York
29 Toronto Argonauts Frank Hoffman DL York

SELECT, WHERE, COUNT, MIN, MAX, AND, >, <, =.
```
Conversational QA

Entity Coreference
- Who is the president of the United States?
- What is its population?
  - Donald Trump

Subsequence Coreference
- Where did the president of the United States born?
- Where did he graduate from?
  - New York City

Relation Ellipsis
- Who is the president of the United States?
- How about China
  - New York City
Neural Network-based Semantic Parsing for Conversational KBQA

(\textit{MSRA-NLC @ NIPS 2018})
Applications in Bing

- Bing Table QA: Answers questions using a table format.
- Bing Knowledge QA: Answers questions using knowledge cards.
Monsoon Restaurant
615 19th Ave E, Seattle, WA 98112
(206) 325-2111
Open until 11:30 PM

More about Monsoon Restaurant
Cuisine: Vietnamese, Chinese

Open
10:00 AM - 11:30 PM

Menu favorites
Caramelized Idaho Catfish Claypot (Seafood)
Crispy Local Drunken Chicken
Crispy Imperial Rolls
Bo la Lot
Carlton Farm Pork Spare Ribs

Featured on
Where to Find 18 of Seattle's Best Desserts
Eater
Seattle's Delightful Dim Sum Restaurants
Eater
10 Vietnamese Dishes You Need to Know
Zagat

Questions? Ask Monsoon Restaurant bot for help
Chat
A summary about QA

1. Big progress was made in question understanding, knowledge graph and answer extraction. QA for simple question has been successfully used in search engine.

2. Traditionally, grammar-based semantic parser was applied, but now encoder-decoder approach becomes mainstreams. But I think that no conclusion can be made on which method is the best.

3. Context-aware semantic parser, as a vital technologies for conversational QA, has achieved promising result, but it needs more efforts in data annotation, modeling and testing.
New trends brought by NLP

• QA
• Multi-lingual
• Multi-modal
• MRC
• Personalized recommendation
NMT research

Rich Resource MT
(Zh-En, Fr-En, De-En,...)

Low Resource MT
(En-He, Fr-Ro, He-Ro,...)

Large Bilingual Corpus

Small or No Bilingual Corpus
$f = (经济, 发展, 变慢了, .)

e = (Economic, growth, has slowed, down, in, recent, years,.)
Neural machine translation

Bahdanau et al., ICLR, 2015
Neural machine translation

Bahdanau et al., ICLR, 2015
Human-Parity results on WMT 2017

- BLEU (%)
  - 24.2 (Transformer Baseline)
  - 25.57 (Back Translation)
  - 26.91 (Agreement Regularization)
  - 26.51 (Dual Learning)
  - 25.57 (Back Translation)
  - 26.38 (Sogou, Ensemble)
  - 24.2 (Transformer Baseline)
  - 25.57 (Back Translation)
  - 26.91 (Agreement Regularization)
  - 26.51 (Dual Learning)
  - 28.46 (System Combination)
  - 27.40 (Deliberation Nets)
  - 27.71 (Joint Training)
  - 25.57 (Back Translation)

Graph showing the progress over time:
- Sep. to Oct.: 24.2
- Oct. to Nov.: 25.57
- Nov. to Dec.: 26.91
- Dec. to Jan.: 26.51
- Jan. to Feb.: 28.46
- Feb. to Mar.: 27.40
- Mar. to Apr.: 27.71
### News translation results

- Sampled from WMT2017 Chinese-English task

<table>
<thead>
<tr>
<th>Source input</th>
<th>有线索人士请拨打旧金山警察局举报电话415-575-4444。</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMT output</td>
<td>For clues, call the San Francisco Police Department at 415-575 - 4444.</td>
</tr>
<tr>
<td>Human reference</td>
<td>Anyone with information is asked to call the SFPD Tip Line at 415-575-4444.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source input</th>
<th>他的职业生涯如过山车一般。</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMT output</td>
<td>It has been a rollercoaster ride.</td>
</tr>
<tr>
<td>Human reference</td>
<td>His career is like a roller coaster.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source input</th>
<th>霍夫施泰特尔表示:&quot;这将由检察官来确定&quot;。</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMT output</td>
<td>&quot;That's what the prosecutor must determine,&quot; said Hofstetter.</td>
</tr>
<tr>
<td>Human reference</td>
<td>Mr Hoff Steitel said: &quot;It will be up to the prosecutors to determine.&quot;</td>
</tr>
</tbody>
</table>
Term translation mining

News stream data
Chs  Enu  History  Current

Burst distribution

"金刚狼" (漫威漫画出版物中的英雄角色)

中文名  金刚狼
英文名  The Wolverine
出生地  加拿大

特金会

the Trump-Kim meeting
Low-resource neural machine translation

Pivot-based NMT

\[
p(y|x) = \sum_{z \in Z} p(z|x)p(y|z)
\]

\[
p(x|y) = \sum_{z \in Z} p(z|y)p(x|z)
\]

To translate a Chinese sentence \( x \) to a Japanese sentence \( z \), we first translate \( x \) to an English sentence \( y \), then translate \( y \) to Japanese \( z \).

Tri-Language NMT

Language \( Z \) is the hidden space between language \( X \) and language \( Y \).

\[
p(y|x) = \sum_{z \in Z} p(z|x)p(y|z)
\]

\[
p(x|y) = \sum_{z \in Z} p(z|y)p(x|z)
\]

EM training is leveraged for fine tuning.

Unsupervised NMT


Ren, et al., 2018. Triangular architecture for rare language translation

Ren, et al., 2018. Unsupervised neural machine translation with SMT as posterior regularization. Submitted
A summary about multi-lingual search

1. Amazing progress in rich language translation at single-sentence level, such as news translation.
2. We have witnessed some progress in low-resource language translation, but it is still at very early stage. I think that it will be the most important topic in NMT.
3. We need to develop better models for term translation and query translation.
New trends brought by NLP

- QA
- Multi-lingual
- **Multi-modal**
- MRC
- Personalized recommendation
The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) evaluates algorithms for object detection and image classification at large scale.
I think it's a man flying a kite on the beach.

I think it's a colorful bird perched on a tree branch.

I think it's a boat that is lit up at night in a city.

I think it's a little boy sitting in front of a birthday cake and he seems 😊.
A car is running

A man is cutting a piece of meat

A man is performing on a stage

A man is riding a bike

A man is singing

A panda is walking

A woman is riding a horse

A man is flying in a field
Visual question answering (VQA)

Given an **image** and a related **question**, predict the most possible **answer**

**question**

What sport is the boy playing?

**answer**

baseball

VQA dataset (Agrawal et al., 2016), which contains ~0.25M images, ~0.76M questions, and ~10M answers.
A typical VQA framework

"What sport is the boy playing?"

The size of answer candidates is ~3,000.
Motivating example of using knowledge

- Image mis-understanding due to relation missing

**Question:** what is the girl holding?

**Ground Truth Answer:** racket

**Predicted Answer:** [hand: 0.630] [racket: 0.21] [cone: 0.072] [mouse: 0.004]

If we know (girl, hold, racket) is valid, and (girl, hold, hand) is not valid, we probably can infer “racket” as a better answer.
“what is the girl holding?”

(A) Context-aware Attention

(B) Relation Mining

(C) Fact-aware Attention

(D) Joint Learning

By introducing knowledge, we obtain +1.3 improvement (acc@1) on VQA dataset, and +2.5 improvement (acc@1) on COCO QA dataset.

VQA with knowledge mining examples

Q: Does this building have a clock?
A: yes
R: (clock, on, building) 0.81
   (window, on, building) 0.07
   (building, has, clock) 0.03
   (clock, near, tower) 0.01
   (clock tower, near, building) 0.01
(a)

Q: What are the animals standing on?
A: grass
R: (animal, standing on, grass) 0.27
   (animal, standing on, field) 0.20
   (zebra, standing on, grass) 0.19
   (zebra, standing on, field) 0.14
   (animal, standing on, gazing) 0.13
(b)

Q: What color is the ball?
A: yellow
R: (ball, is, yellow) 0.43
   (tennis ball, is, yellow) 0.36
   (ball, is, green) 0.12
   (there, is, tennis ball) 0.05
   (ball, in, air) 0.02
(c)

Q: What kind of court is this?
A: tennis court
R: (there, is, tennis court) 0.52
   (white lines, in, tennis court) 0.21
   (line, in, tennis court) 0.09
   (grass, in, tennis court) 0.08
   (court, is, orange) 0.03
(d)
Image retrieval

Melania Trump
Melania Trump is the current First Lady of the United States and wife of the 45th U.S. President Donald Trump.
Image query:

Search Engine
What Elephants Eat. An elephants size means that, when it is fully grown, it is safe from all predators other than humans. To support its large size it needs huge amounts of food. An adult elephant eats about 150 kg (300 lb) of grass, leaves, twigs and fruit each day.

What Elephants Eat And Drink - Live Animals List
A summary about multi-modal search

1. Recent progress of ImageNet and image captioning inspires researchers to conduct research on multi-modal understanding and search.
2. VQA is still at very early stage. There are many challenging topics such as use of knowledge and common sense.
3. There are a few applications in search engine but all are very simple. We expect that with the technologies continually advance, new scenarios will appear.
New trends brought by NLP

- QA
- Multi-lingual
- Multi-modal
- MRC
- Personalized recommendation
Tesla later approached Morgan to ask for more funds to build a more powerful transmitter. *When asked where all the money had gone, Tesla responded by saying that he was affected by the Panic of 1901, which he (Morgan) had caused.* Morgan was shocked by the reminder of his part in the stock market crash and by Tesla’s breach of contract by asking for more funds.

**Question (Q):** On what did Tesla blame for the loss of the initial money?

**Answer (A):** Panic of 1901
In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall? gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail? graupel

Where do water droplets collide with ice crystals to form precipitation? within a cloud

**SQuAD: 100,000+ Questions for Machine Comprehension of Text**

Best Resource Paper in EMNLP 2016

Pranav Rajpurkar and Jian Zhang and Konstantin Lopyrev and Percy Liang

{pranavp,zjian,klopyrev,pliang}@cs.stanford.edu

Computer Science Department

Stanford University

<table>
<thead>
<tr>
<th>Dataset</th>
<th># of &lt;question, passage&gt; pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>87,599</td>
</tr>
<tr>
<td>Dev</td>
<td>10,570</td>
</tr>
<tr>
<td>Test (not available to participants)</td>
<td>&gt; 10K</td>
</tr>
</tbody>
</table>

*ImageNet* style competition for machine reading comprehension
Progress of MRC experiments

Human EM Performance: 82.304

Best System EM Scores on SQuAD Machine Reading Comprehension Dataset (Dec. 6, 2016-Jan. 26, 2018)

Surpass Human EM [2018.1.3]
MRC architecture (r-net)

Embedding Layer
- Pretrained Word Embeddings

Encoding Layer
- RNN( GRU, LSTM) + Highway

Matching Layer
- Match-LSTM Co-attention

Self-Matching Layer
- Self-Attention

Answer Pointer Layer
- Pointer Networks MLP & Softmax + Iteratively

Contextualized Vectors
(e.g. RNN encoders from NMT and LM)

e.g., ELMo – Embeddings from Language Models
Who created Microsoft Word?

The first version of Microsoft Word was developed by Charles Simonyi and Richard Brodie, former Xerox programmers hired by Bill Gates and Paul Allen in 1981.

History of Microsoft Word - Wikipedia
en.wikipedia.org/wiki/History_of_Microsoft_Word
Contents

The fastest way to find information on a particular topic or item is by using the index, refer to page 146.

Using this Owner's Manual

4 Notes
6 Reporting safety defects

At a glance

10 Cockpit

Controls

18 Opening and closing
31 Adjustments
39 Transporting children safely
42 Driving
57 Everything under control
65 Technology for driving comfort and safety
74 Lamps
78 Climate
84 Practical interior accessories

Driving tips

96 Things to remember when driving

Mobility

104 Refueling
106 Wheels and tires
112 Under the hood
117 Maintenance
119 Replacing components
125 Giving and receiving assistance
130 Indicator and warning lamps

Reference

142 Technical data
146 Everything from A to Z
You can also call BMW of North America at 1-800-831-1117 or visit the website [www.bmwusa.com](http://www.bmwusa.com) to obtain this information.

**Viscosity ratings**

Viscosity is a measure of an oil's flow rating and is categorized in SAE classes.

Selecting the appropriate SAE class depends on the regional climatic conditions in which you normally drive your BMW. Approved oils belong to the 5W-40 and 5W-30 classes.

These oils can be used for driving at all outside temperatures.

**Coolant**

Do not add coolant to the cooling system when the engine is hot. Escaping coolant can cause burns.

Coolant is a mixture of water and an additive. Not all commercially available additives are suitable for your BMW. Ask your BMW Center for suitable additives.

Use suitable additives, otherwise engine damage may result. The additives are hazardous to your health.

Comply with the appropriate environmental protection regulations when discarding antifreeze.

**Brake system**

**Malfunctions**

**Brake fluid**

The warning lamps light up in red even though the handbrake has been released. Stop immediately.

The brake fluid in the reservoir has fallen to below the minimum level. At the same time, a considerably longer brake pedal travel may be noticeable. Have the system checked without delay.

**Display of this malfunction on Canadian models.**
Microsoft Surface Pro 4 (128 GB, 4 GB RAM, Intel Core i5)

by Microsoft

4.5 stars – 1,623 customer reviews | 820 answered questions

Price: $775.00 & FREE Shipping

In Stock.

Get it as soon as Wednesday, March 1 when you choose Two-Day Shipping at checkout. Ships from and sold by PreBase USA.

Style: Device Only
Size: Intel Core i5, 4GB RAM, 4GB
Used & new (78) from $629.99 & FREE shipping.

Customer Questions & Answers

Question: should I buy one with 8gb? I think if you’re a regular 128gb card in for $60. I am getting a newer model now. By Devon on November 1
Answer: See more answers (9)

Question: So if I want more storage. Yes, I am using SP4 with point, for now, unless you this feature in the future. By WX on October 30, 2016
Answer: 18 votes

Customer Reviews

Top Customer Reviews

I love it, but you might not. By Jeshua Oh on October 28, 2015

Style Name: Device Only | Size: Intel Core i5, 8GB RAM, 256GB

It seems like the big question right now is, "Do I get the Surface Pro 4?" I’ll explain why I chose the Surface Pro 4, but first, a quick about having a light backpack is important to me.

The S.Book is almost two times heavier than the SP4. It packs extra power that the S.Book has. I don’t plan to play any intense games it only has a $400 higher price tag ($270 if you get the Type Cover for S.Book’s keyboard, but the SP4’s keyboard feels great to type on and other PDF’s feels much more natural with the SP4’s table.

Does it have an HDMI port?

It has a mini display port, but through the use of an adapter this will allow an HDMI connection.
A summary about MRC

1. Recently we’ve seen a big progress in MRC, such as SQuAD evaluation. End-end training, pre-trained models, contextualized vectors from other tasks contribute to the growth of MRC.
2. MRC will significantly change search engine with better relevance and accuracy. New scenarios such as manual search are promising.
3. Further developing MRC needs contextual inference supported by knowledge and common sense. This would be very challenging and exciting.
New trends brought by NLP

- QA
- Multi-lingual
- Multi-modal
- MRC
- Personalized recommendation
Personalized feed: go beyond search
User modeling with behavioral data
Personalized recommendation

User Modeling

Item (news, blogs, videos)

Personalization

Feed

Text Understanding in User and Item Modeling

Knowledge Aware Recommendation

Text Generation
Applications

- Xiting Wang, Yiru Chen, Jie Yang, etc. A Reinforcement Learning Framework for Explainable Recommendation, ICDM 2018
- Hongwei Wang, Fuzheng Zhang, Jialin Wang, etc. Ripple Network: Propagating User Preferences on the Knowledge Graph for Recommender Systems, CIKM 2018
- Jianxun Lian, Xiaohuan Zhou, etc., xDeepFM: Combining Explicit and Implicit Feature Interactions for Recommender Systems, KDD 2018
- Zheng Liu, Xing Xie, Lei Chen, Context-aware Academic Collaborator Recommendation, KDD 2018
- Jianxun Lian, etc. Towards Better Representation Learning for Personalized News Recommendation: a Multi-Channel Deep Fusion Approach, IJCAI 2018
- Guanjie Zheng, Fuzheng Zhang, Zihan Zheng, etc. DRN: A Deep Reinforcement Learning Framework for News Recommendation, WWW 2018
- Hongwei Wang, Fuzheng Zhang, Xing Xie, Minyi Guo, DKN: Deep Knowledge-Aware Network for News Recommendation, WWW 2018
A summary about personalized recommendation

1. Personalized recommendation has become the strategically important for search companies.
2. There are many interesting research topics in user modelling with various user behavior data, timely recommendation of user-like contents, providing personalized recommendation comments.
With new advancements of NLP, what new changes will be brought to search?

- QA
- Multi-lingual
- Multi-modal
- MRC
- Personalized recommendation

However, there are many challenges to each of these tasks and there are still long way to make them convincingly become the integral parts of search engine to reach good user experience. We should have enough patience in pushing forward these directions.
Future research topics

• Knowledge acquisition and representation
  • word/sentence embedding, commonsense knowledge, specific domain knowledge, knowledge graph

• New learning methods
  • Multi-task and transfer learning, reinforcement learning, semi and unsupervised learning for low-resource tasks, reasoning for MRC

• Context modeling
  • Multi-turn modeling, context-aware semantic parser, dialogue system

• New search modality
  • Conversational search, multi-modal search

• Search results generation and summarization
  • Auto-generation of a comprehensive report for certain type of queries

• Feeds
  • User modelling, content generation, recommendation, comments
A big thanks go to my colleagues and students in MSRA who are working on various NLP tasks mentioned in this talk, especially Nan Duan, Shujie Liu, Dongdong Zhang, Furu Wei and Xing Xie.