QMUL Cognitive Science & Computational Linguistics

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Cognitive Science at QMUL

“human cognition, action and interaction on scales ranging from individual experience, through interactions between individuals to the languages, cultures and dynamics of societies.”
Cognitive Science in HCl

<table>
<thead>
<tr>
<th>Long-Term Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>( h_{LTM} = )</td>
</tr>
<tr>
<td>( k_{LTM} = )</td>
</tr>
<tr>
<td>( \kappa_{LTM} = ) semantic</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Working Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Visual Image Store</strong></td>
</tr>
<tr>
<td>( \delta_{VIS} = 300 ) [70–1000] msec</td>
</tr>
<tr>
<td>( \mu_{VIS} = 17 ) [7–17] letters</td>
</tr>
<tr>
<td>( \kappa_{VIS} = ) Physical</td>
</tr>
</tbody>
</table>

| **Auditory Image Store** |
| \( \delta_{AIS} = 1500 \) [800–3500] msec |
| \( \mu_{AIS} = 5 \) [4.4–8.2] letters |
| \( \kappa_{AIS} = \) Physical |

<table>
<thead>
<tr>
<th>Working Memory</th>
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</thead>
<tbody>
<tr>
<td><strong>Visual WM</strong></td>
</tr>
<tr>
<td>( \mu_{WM} = ) 3 [2.5–4.1] chunks</td>
</tr>
<tr>
<td>( \delta_{WM} = ) 7 [5–22] sec</td>
</tr>
<tr>
<td>( \delta_{WM}(1 \text{ chunk}) = 73 ) [73–220] sec</td>
</tr>
<tr>
<td>( \delta_{WM}(3 \text{ chunks}) = 7 ) [5–34] sec</td>
</tr>
<tr>
<td>( \kappa_{WM} = ) Acoustic or Visual</td>
</tr>
</tbody>
</table>

Perceptual Processor: \( \tau_p = 70 \) [25–170] msec

Motor Processor: \( \tau_m = 70 \) [50–100] msec

Eye movement: 230 [70–700] msec
Understanding Music
Computational Creativity

DS-TTR

SE/GENERATION

STATE GRAPH

CONCEPT GRAPH

(OUTPUT)
Computational Magic

Magic trick design and evaluation framework

Jigsaw pieces are numbered to highlight rearrangement

Card trick tree structure - simple example

Initial deck - cyclic sequence defined by colour of cards - sequence length 2

Cards dispensed in pairs

Each leaf node is a unique tuple of red and/or black

User evaluation

User validation - sales to magicians
Language
Therapy Communication

Yeh, it doesn’t happen in real life, does it?

What do you mean by real life?

You can’t—there are no messages coming from the television to people are there?
Computational Linguistics

• Computational semantics:
  – Relating language to meaning
    • “sandy likes kim” vs like(s’, k’)

• Computational pragmatics:
  – Relating language to its function
    • “does sandy like kim?”

• Human-computer language
  – Computers that can talk to humans

• Human-human language
  – Computers that can understand human talk
Language is complicated

• It has structure:
  
  *dog bites man*
  
  *man bites dog*

• It involves meaning:
  
  *dog chases cats*
  
  *puppy pursues kittens*

• Meaning depends on structure:
  
  *no dog chases cats*
  
  *no dog chases cats slowly*
  
  *no idea if dog chases cats*
It’s not just about the words

• Structural dependencies
• E.g. negation

```
justin’s new hair is nice
justin’s new hair is not nice
justin’s new hair is not very nice
justin’s new hair is not as nice
justin’s new hair is not really all that nice
justin’s new hair is not short but very nice
```
Linguistic Analysis

words: mary hires a detective

parts of speech: PN VBZ DET CN

syntax:
\[ S \rightarrow NP \rightarrow VP \]

semantics:
\[ \exists e, x . hire(e) \land subj(e, mary) \land obj(e, x) \land detective(x) \]
Linguistic Analysis

• Meaning is often what we’re interested in
• How do we understand:
  – Subjective vs objective statements
  – Statements of fact
  – Positive vs negative stance
  – Anger vs sadness vs disappointment vs ...
  – Topic of conversation
  – Expression of opinions
  – Expression of intentions
• Words are not enough!
Two main approaches

• Structure vs statistics:

mary hires a detective
PN VBZ DET CN

S VP NP
Statistical Models

• Binary classification e.g. SVMs for sentiment

- i love @justinbieber #sarcasm
Computational analysis

- Syntactic & semantic parsing
  - (Probabilistic) grammar rules:
    - \( S \rightarrow NP \ VP \)
    - \( VP \rightarrow VBZ \ NP \)
    - \( NP \rightarrow DET \ CN \)
    - ...
  - (Probabilistic) parsing algorithm
  - Syntax-semantics correspondences
  - Good accuracy c. 80-90%
    - See e.g. (Clark & Curran, 2007)
  - But: written (mostly) by hand, or learnt from specific datsets
Human-Computer Dialogue

A: Ticket to London in March
B: OK

A: I want to go to er
B: yes
A: to London
B: London?
A: sorry no Paris, in March

- Incrementality
  - Semantic parsing and generation
  - DYLAN dialogue system

- Coordination and repair
  - Self-repair, other-repair, clarification
Incremental Grammar Induction

- Induction from semantics
  - for an incremental grammar
  - with incremental learning
  - 92% coverage, 85% F-score on CHILDES

\[ x = \text{john} \]
\[ y = \text{mary} \]
\[ p = \text{upset}(x,y) \]
Incremental dialogue: DyLAN

- Dynamic Syntax
- Type Theory with Records
  - (IWCS 2011, TTNLS 2014)

```
I want to go to Paris
...
```

```
e = now : e_s

e1 = future : e_s

x1 = Paris : e

p2 = to(e1, x1) : t

x = speaker : e

p1 = go(e1, x) : t

p = want(e, x, p1) : t
```
Online language

Nyt alexx tweetdreamsh RT @JDBAustralia: Goodnight everyone, i will tweet you all tomorrow <3 #loveislouder

Im Not Goin o2 Be Sad o2day Imah $MILE , Jus o4 Big Bruhh!

LOL IM BOR3D @ENYCHARM YU GOIN O2 DA M33TING?
Online conversations

i love marmite :)  
i hate it  
toast #fail  
it’s amazing!!!! <3  
best spread evaaaaa
Live London Emotion Map

http://www.eecs.qmul.ac.uk/~mpurver/emomap/

(happy = yellow, sad = blue, angry = red)
‘Beacon’ @ Skysong Center

‘Emotional weather’ for Phoenix, AZ - www.edpurver.com
Barbican CMSI

- Understand audiences better
- Relate to offerings across artistic genres
- Locate curious audience members and learn from them
- Diversify audiences
- As automatically as possible
- Twitter: naturally occurring conversation as opposed to surveys etc
Relevance Filtering

Ludovico Einaudi, Barbican, review: The composer's flexible show blended full-band gallops with eerily spaciou... http://t.co/qxs1vPnf

Stand-up @MrEdByrne is in his Roaring Forties and coming to the York Barbican this October! http://t.co/qu1HpGHyn7

I miss Bank Holidays on the Barbican #drunk #memories #Plymouth @Kimbletron Rub it in.. I wish I was down there on the Barbican with a big ice lolly.

I swear @Shuhzia is so dumb, she thought I was drinking alcohol -.- it's Barbican, non alcoholic, ARABIC beverage

Pomegranate barbican is an addiction♡

Something going on at Barbican station about 12 emergency vehicles there mostly fire engines :-/
Topic Discovery

- tonight london night einaudi live ludovicoeinaud mogwai concert zidane
- london create art music festival centre city openeast weekend dance great
- street visit centre selling pay pop page tickets click albums london
- road cloud ix saturday july drink tonight celebration party deh life beer
- love tower interesting mark building em hate goldfinger shard division
- film london ideastap films aged short festival framed urban wandering
- hackthebarbican hack pm hacktb today week uk part dollop centre august
- plymouth plymbarbican day time today great hoe good lunch nice night
- london zorn show house dalstonhouse dalston john ticket september
- room gin drink rain drinks cinema haha school class trade bottle apple
- ...

Cognitive Science Research Group
http://cogsci.eecs.qmul.ac.uk
Finding Interests

- Relevance filtering; 95% accurate
- Topic discovery:
  - artistic genres
  - sentiment

<table>
<thead>
<tr>
<th>‘Enjoyment’</th>
<th>‘Ludovico’</th>
<th>‘HTB’</th>
<th>‘Gigs’</th>
<th>‘Festival’</th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>einaudi</td>
<td>hackthebarbican</td>
<td>mogwai</td>
<td>london</td>
</tr>
<tr>
<td>good</td>
<td>ludovicoeinaud</td>
<td>uk</td>
<td>tickets</td>
<td>create</td>
</tr>
<tr>
<td>love</td>
<td>night</td>
<td>dollop</td>
<td>zidane</td>
<td>festival</td>
</tr>
<tr>
<td>lunch</td>
<td>tonight</td>
<td>hack</td>
<td>tonight</td>
<td>openeast</td>
</tr>
<tr>
<td>day</td>
<td>ludovico</td>
<td>today</td>
<td>live</td>
<td>park</td>
</tr>
<tr>
<td>back</td>
<td>amazing</td>
<td>jackmaster</td>
<td>mogwaband</td>
<td>weekend</td>
</tr>
<tr>
<td>walk</td>
<td>concert</td>
<td>part</td>
<td>devendra</td>
<td>olympic</td>
</tr>
<tr>
<td>night</td>
<td>music</td>
<td>loefah</td>
<td>london</td>
<td>east</td>
</tr>
<tr>
<td>nice</td>
<td>time</td>
<td>htb</td>
<td>banhart</td>
<td>music</td>
</tr>
<tr>
<td>haha</td>
<td>evening</td>
<td>free</td>
<td>bought</td>
<td>open</td>
</tr>
</tbody>
</table>
Mental Health

- Analysing language and conversation in therapy
- Schizophrenia: face-to-face outpatient consultations
- Depression & anxiety: online text-based CBT
Repair in Therapy Dialogue

• Self-repair:

Dr: You probably have seen so many psychiatrists o o over the years

Dr: Did you feel that did you despair so much that you wondered if you could carry on

• Other-repair:

Dr: Rather than the diazepam which I don’t think is going to do you any good
P: the valium

Dr: Yeh, it doesn’t happen in real life does it?
P: What do you mean by real life?
Dr: You can’t - there are no messages coming from the television to people are there?
## Automatic topic modelling

- Infer 20 lexical “topics”:

<table>
<thead>
<tr>
<th>Topic</th>
<th>Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>feel low alright mood long drug feeling tired time confident</td>
</tr>
<tr>
<td>4</td>
<td>voices pills mood cannabis telly voice shaking chris control</td>
</tr>
<tr>
<td>5</td>
<td>letter health advice letters council copy send dla cpn prob</td>
</tr>
<tr>
<td>7</td>
<td>church voice voices hear medication sister bad hearing take</td>
</tr>
<tr>
<td>9</td>
<td>school children kids back september oclock gonna phone see</td>
</tr>
<tr>
<td>10</td>
<td>weight months medication stone risk lose eat write gp has</td>
</tr>
<tr>
<td>11</td>
<td>place support work centre gotta job stress feel psychologist</td>
</tr>
<tr>
<td>12</td>
<td>door house police thought ring knew worse wall hadnt sad</td>
</tr>
<tr>
<td>13</td>
<td>doctor alright years nice ill anxious write long sit eye hear</td>
</tr>
<tr>
<td>14</td>
<td>drug taking milligrams hundred doctor night time medication</td>
</tr>
<tr>
<td>15</td>
<td>sort medication work drugs kind team issues drink alcohol</td>
</tr>
<tr>
<td>16</td>
<td>mum place brother tablets died dad depot house meet mom</td>
</tr>
<tr>
<td>17</td>
<td>people life drug make care lot friends dry camera live copy</td>
</tr>
<tr>
<td>18</td>
<td>alright house drink drinking money alcohol god drugs living</td>
</tr>
</tbody>
</table>
Predicting outcomes

- Schizophrenia: doctor/patient ratings:
  - PANSS positive symptom scale: 60% accurate
  - HAS Helping Alliance Scale: 75% accurate

- Schizophrenia: adherence to treatment in 6 months:

<table>
<thead>
<tr>
<th>Data</th>
<th>P (%)</th>
<th>R (%)</th>
<th>F (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human expert with text</td>
<td>60.3</td>
<td>79.6</td>
<td>68.6</td>
</tr>
<tr>
<td>Automatic</td>
<td>70.3</td>
<td>70.3</td>
<td>70.3</td>
</tr>
<tr>
<td>Human expert with video</td>
<td>69.6</td>
<td>88.6</td>
<td>78.0</td>
</tr>
</tbody>
</table>

- Depression:
  - final in-caseness: 70-75%
  - dropout: 73%
Thanks!