Outline

Morning program
- Preliminaries
- Text matching I
- Text matching II

Afternoon program
- Learning to rank
- Modeling user behavior
- Generating responses
- Wrap up

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General Formulation of Typical DL Models

The general basic formulation:

- Learnable parametric function
- Inputs: generally considered I.I.D.
- Outputs: classification or regression

Question: Is this enough?

Example Scenario

Joe went to the kitchen. Fred went to the kitchen. Joe picked up the milk. Joe traveled to the office. Joe left the milk. Joe went to the bathroom.

- Where is the milk now? A: office
- Where is Joe? A: bathroom
- Where was Joe before the office? A: kitchen

What is Required?

- The model needs to remember the context
- Given an input, the model needs to know where to look for in the context
- It needs to know what to look for in the context
- It needs to know how to reason using this context
- It needs to handle the potentially changing the context
- A Possible Solution:
  - Hidden states of RNNs have memory: Run an RNN on the context/story/KB and get its representation. Then use the representation to map question to answers/response.
    - will not scale as RNN don't have ability to capture long term dependency: Vanishing gradient, The state of memory is not large enough to capture rich information

Neural Networks with Memory

- Memory Networks
  - Fully Supervised MemNNs
  - End2End MemNNs
  - Key-Value MemNNs
- Neural Turing Machines
- Stack/List/Queue Augmented RNNs

Memory Networks

Class of models which combine large memory with learning component which can read and write to it.

- Step 1: controller converts incoming data to internal feature representation (I)
- Step 2: write head updates the memories and writes the data into memory (G)
- Step 3: given the external input, the read head reads the memory and fetches relevant data (O)
- Step 4: controller combines the external data with memory contents returned by read head to generate output (O, R)
- Inference Given the question, picks the memory which scores the highest and uses the selected memory and the question to generate the answer.

Fully Supervised Memory Networks [Weston et al., 2015]

- Current supporting facts are supplied as supervision signal for learning the memory addressing stage:
  - It is essentially like hard attention except that you already know where to attend!

Fully Supervised Memory Networks

Context:

John was in the bathroom.

Bob was in the office.

John went to the kitchen. $\Longrightarrow$ Supporting Fact

Bob traveled back home.

Question Answer Pair:

Where is John? A: **kitchen**

End2End Memory Networks [Sukhbaatar et al., 2015]

- No current supporting fact supplied.
- Learns which parts of the memory are relevant.
- This is achieved by reading using soft attention as opposed to hard.
- Performs multiple lookups to refine its guess about memory relevance.
- Only needs supervision at the final output.

End2End Memory Networks (Multiple Hops)

$$p_i = Softmax(u^T m_i)$$

$$o = \sum_i p_i c_i$$

$$\hat{a} = Softmax(W(o+u))$$

$${}^k p_i = Softmax({}^k u^T \cdot {}^k m_i)$$

$${}^k o = \sum_i {}^k p_i {}^k c_i$$

$${}^{k+1} u = {}^k u + {}^k o$$

$$\hat{a} = Softmax(W \cdot {}^{k+1} u) = Softmax(W({}^k o + {}^k u))$$

- Share the input and output embeddings or not
- What to store in memories individual words, word windows, full sentences
- How to represent the memories bag-of-words, RNN style reading at words or characters

Attentive Memory Networks [Kenter and de Rijke, 2017]

- Proposed Model: An end-to-end trainable memory networks with a hierarchical input encoder.

- Framing the task of conversational search as a general machine reading task.

Key-Value Memory Networks [Miller et al., 2016]

$m_i = (k_i, v_i)$

Address: score k_i vs. q

Read: return v_i

- Facts are stored in a key value structured memory.
- Memory is designed so that the model learns to use keys to address relevant memories with respect to the question.
- Structure allows the model to encode prior knowledge for the considered task.
- Structure also allows to leverage possibly complex transforms between key and value.

Key-Value Memory Networks

Example:

for a KB triple [subject, relation, object], Key could be [subject,relation] and value could be [object] or vice versa.

Machine Reading [Hermann et al., 2015]

Cloze Style Question Answering:
Teaching a machine to understand language. To read a comprehension and answer questions pertaining to it. However, the questions should be such that they cannot be answered using external world knowledge.

Original Version	Anonymised Version
Context	
The BBC producer allegedly struck by Jeremy Clarkson will not press charges against the "Top Gear" host, his lawyer said Friday. Clarkson, who hosted one of the most-watched television shows in the world, was dropped by the BBC Wednesday after an internal investigation by the British broadcaster found he had subjected producer Oisin Tymon "to an unprovoked physical and verbal attack." ...	the *ent381* producer allegedly struck by *ent212* will not press charges against the " *ent153* " host , his lawyer said friday . *ent212* , who hosted one of the most - watched television shows in the world , was dropped by the *ent381* wednesday after an internal investigation by the *ent180* broadcaster found he had subjected producer *ent193* " to an unprovoked physical and verbal attack . " ...
Query	
Producer **X** will not press charges against Jeremy Clarkson, his lawyer says.	producer **X** will not press charges against *ent212* , his lawyer says .
Answer	
Oisin Tymon	*ent193*

Teaching Machine to Read and Comprehend

General Structure: A two layer Deep LSTM Reader with the question encoded before the document:

(a) Attentive Reader.

(b) Impatient Reader.

Document Attentive Reading:

by *ent423* , *ent261* correspondent updated 9:49 pm et , thu march 19 , 2015 (*ent261*) a *ent114* was killed in a parachute accident in *ent45* , *ent85* , near *ent312* , a *ent119* official told *ent261* on wednesday . he was identified thursday as special warfare operator 3rd class *ent23* , 29 , of *ent187* , *ent265* . `` *ent23* distinguished himself consistently throughout his career . he was the epitome of the quiet professional in all facets of his life , and he leaves an inspiring legacy of natural tenacity and focused

. . .

ent119 identifies deceased sailor as **X** , who leaves behind a wife

by *ent270* , *ent223* updated 9:35 am et , mon march 2 , 2015 (*ent223*) *ent63* went familial for fall at its fashion show in *ent231* on sunday , dedicating its collection to `` mamma " with nary a pair of `` mom jeans " in sight . *ent164* and *ent21* , who are behind the *ent196* brand , sent models down the runway in decidedly feminine dresses and skirts adorned with roses , lace and even embroidered doodles by the designers ' own nieces and nephews . many of the looks featured saccharine needlework phrases like `` i love you ,

. . .

X dedicated their fall fashion show to moms

WikiReading [Hewlett et al., 2016]

Task:

To predict textual values from the structured knowledge base Wikidata by reading the text of the corresponding Wikipedia articles.

	Categorization		Extraction	
Document	Folkart Towers are twin skyscrapers in the Bayrakli district of the Turkish city of Izmir. Reaching a structural height of 200 m (656 ft) above ground level, they are the tallest ...	Angeles blancos is a Mexican telenovela produced by Carlos Sotomayor for Televisa in 1990. Jacqueline Andere, Rogelio Guerra and Alfonso Iturralde star as the main ...	Canada is a country in the northern part of North America. Its ten provinces and three territories extend from the **Atlantic** to the **Pacific** and northward into the **Arctic Ocean**, ...	Breaking Bad is an American crime drama television series created and produced by Vince Gilligan. The show originally aired on the AMC network for five seasons, from **January 20, 2008**, to ...
Property	country	original language of work	located next to body of water	start time
Answer	Turkey	Spanish	Atlantic Ocean, Arctic Ocean, Pacific Ocean	20 January 2008

- Categorical: properties, such as instance of, gender and country, require selecting between a relatively small number of possible answers.
- Relational: properties, such as date of birth, parent, and capital, typically require extracting rare or totally unique answers from the document.

WikiReading

- **Answer Classification**: Encoding document and question, using softmax classifier to assign probability to each of to-50k answers (limited answer vocab) .
  - Sparse BoW Baseline, Averaged Embeddings, Paragraph Vector, LSTM Reader, Attentive Reader, Memory Network.
  - Generally models with RNN and attention work better, especially at relational properties.
- **Answer Extraction** (labeling/pointing) For each word in the document, compute the probability that it is part of the answer.
  - Regardless of the vocabulary so the answer requires being mentioned in the document.
  - RNN Labeler: shows a complementary set of strengths, performing better on relational properties than categorical ones
- **Sequence to Sequence** Encoding query and document and decoding the answer as sequences of words or characters.
  - Basic seq2seq, Placeholder seq2seq, Basic Character seq2seq,
  - Unifies the classification and extraction in one model: Greater degree of balance between relational and categorical properties.

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Dialogue systems

Dialogues/conversational agents/chat bots

Open-ended dialogues

- ELIZA
- Twitterbots
- Alexa/Google home/Siri/Cortana

Goal-oriented dialogues

- Restaurant finding
- Hotel reservations
- Set an alarm clock
- Order a pizza
- Play music
- Alexa/Google home/Siri/Cortana

Is this IR?

Dialogue systems

Chit-chat bots

Straightforward seq-to-seq [Vinyals and Le, 2015].
([Sordoni et al., 2015b] is a precursor, but no RNN-to-RNN, and no LSTM).

Same idea, but with attention [Shang et al., 2015]

Dialogue systems

Limitations

- 'Wrong' optimization criterion
- Generic responses
- No way to incorporate world knowledge
- No model of conversation
  - Inconsistency
  - No memory of what was said earlier on

Human: *what is your job?*
Machine: *i'm a lawyer.*
Human: *what do you do?*
Machine: *i'm a doctor.*
Example from [Vinyals and Le, 2015]

Evaluation

- Perplexity?
- BLUE/METEOR?
- Nice overview of *How NOT To Evaluate Your Dialogue System* [Liu et al., 2016].
- Open problem....

Dialogue systems

4 solutions

- More consistency by maintaining a persona
- More consistency in dialogue with hierarchical network
- Less generic responses with different optimization function
- More natural responses with GANs

Persona-based

A persona-based model for generating responses [Li et al., 2016].

Dialogue systems

Hierarchical seq-to-seq [Serban et al., 2016]. Main evaluation metric: perplexity.

Dialogue systems

Avoid generic responses

Usually: optimize log likelihood of predicted utterance, given previous context:

$$C_{LL} = \arg\max_{u_t} log\, p(u_t|\textit{context}) = \arg\max_{u_t} log\, p(u_t|u_0 \dots u_{t-1})$$

To avoid repetitive/boring answer (*I don't know*), use maximum mutual information between previous context and predicted utterance [Li et al., 2015].

$$\begin{aligned} C_{MMI} &= \arg\max_{u_t} log \frac{p(u_t, \textit{context})}{p(u_t)p(\textit{context})} \\ &= \textit{[derivation, next page ...]} \\ &= \arg\max_{u_t} (1-\lambda) log\, p(u_t|\textit{context}) + \lambda log\, p(\textit{context}|u_t) \end{aligned}$$

Dialogue systems

Bayes rule

$$log\, p(u_t|context) = log \frac{p(context|u_t)p(u_t)}{p(context)}$$

$$log\, p(u_t|context) = log\, p(context|u_t) + log\, p(u_t) - log\, p(context)$$

$$log\, p(u_t) = log\, p(u_t|context) - log\, p(context|u_t) + log\, p(context)$$

$$\begin{aligned}
C_{MMI} &= \arg\max_{u_t} log \frac{p(u_t, context)}{p(u_t)p(context)} = \arg\max_{u_t} log \frac{p(u_t|context)p(context)}{p(u_t)p(context)} \\
&= \arg\max_{u_t} log \frac{p(u_t|context)}{p(u_t)} \\
&= \arg\max_{u_t} log\, p(u_t|context) - log\, p(u_t) \leftarrow \text{weird, minus language model score} \\
&= \arg\max_{u_t} log\, p(u_t|context) - \lambda log\, p(u_t) \leftarrow \text{Introduce lambda} \\
&= \arg\max_{u_t} log\, p(u_t|context) - \lambda(log\, p(u_t|context) - log\, p(context|u_t) + log\, p(context)) \\
&= \arg\max_{u_t} (1-\lambda) log\, p(u_t|context) + \lambda log\, p(context|u_t)
\end{aligned}$$

(More is needed to get it to work. See [Li et al., 2015] for more details.)

Generative adversarial network for dialogues

- Discriminator network
  - Classifier: real or generated utterance
- Generator network
  - Generate a realistic utterance

Original GAN paper [Goodfellow et al., 2014].
Conditional GANs, e.g. [Isola et al., 2016].

Generative adversarial network for dialogues

- Discriminator network
  - Classifier: real or generated utterance
- Generator network
  - Generate a realistic utterance

See [Li et al., 2017] for more details.

Code available at `https://github.com/jiweil/Neural-Dialogue-Generation`

Dialogue systems

Open-ended dialogue systems

- Very cool, current problem
- Very hard
- Many problems
  - Training data
  - Evaluation
  - Consistency
  - Persona
  - ...

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Goal-oriented

Idea

- Closed domain
  - Restaurant reservations
  - Finding movies
- Have dialogue system find out what the user wants

Challenges

- Training data
- Keeping track of dialogues
- Handling of out-of-domain words or requests
- Going beyond task-specific slot filling
- Intermingling live API calls, chit chat, information requests, etc.
- Evaluation
  - Solve the task
  - Naturalness
  - Tone of voice
  - Speed
  - Error recovery

Goal-oriented as seq2seq

Memory network [Bordes and Weston, 2017]

- Simulated dataset
- Finite set of things the bot can say
  - Because of the way the dataset is constructed
- Memory networks
- Training: next utterance prediction
- Evaluation
  - response-level
  - dialogue-level

Restaurant Knowledge Base, i.e., a table. Queried by API calls.
Each row = restaurant:

- cuisine (10 choices, e.g., French, Thai)
- location (10 choices, e.g., London, Tokyo)
- price range (cheap, moderate or expensive)
- rating (from 1 to 8)

For words of relevant entity types

- add a trainable entity vector

Goal-oriented as reinforcement learning

A typical reinforcement learning system:

- States S
- Actions A
- State transition function: $T : S, A \rightarrow S$
- Reward function: $R : S, A, S \rightarrow \mathbb{R}$
- Policy: $\pi : S \rightarrow A$

A RL system needs an environment to interact with (e.g., real users).

Typically [Shah et al., 2016]:

- States: agents interpretation of the environment: distribution over user intents, dialogue acts and slots and their values
  - intent(buy_ticket)
  - inform(destination=Atlanta)
  - ...
- Actions: possible communications, and are usually designed as a combination of dialogue act tags, slots and possibly slot values
  - request(departure_date)
  - ...

Goal-oriented as reinforcement learning

Restaurant finding [Wen et al., 2017]:

- Neural belief tracking: distribution over a possible values of a set of slots
- Delexicalisation: swap slot-values for generic token (e.g. *Chinese*, *Indian*, *Italian* $\rightarrow$ *FOOD_TYPE*)

Movie finding [Dhingra et al., 2017]:

- Simulated user
- Soft attention over database
- Neural belief tracking:
  - Multinomial distribution for every column over possible column values
  - RNN, input is dialogue so far, output softmax over possible column values

Reward based on finding the right KB entry.

Goal-oriented

Goal-oriented models

- Currently works primarily in very small domains
- How about multiple speakers?
- Not clear what kind of architecture is best
- Reinforcement learning might be the way to go (?)
- Open research area...

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Resources

Open-ended dialogue

- Opensubtitles [Tiedemann, 2009]
- Twitter: http://research.microsoft.com/convo/
- Weibo:

http://www.noahlab.com.hk/topics/ShortTextConversation

- Ubuntu Dialogue Corpus [Lowe et al., 2015]
- Switchboard

https://web.stanford.edu/~jurafsky/ws97/

- Coarse Discourse (Google Research)

https://research.googleblog.com/2017/05/

coarse-discourse-dataset-for.html

Goal-oriented dialogues

- MISC: A data set of information-seeking conversations [Thomas et al., 2017]
- Maluuba Frames

http://datasets.maluuba.com/Frames

- Loqui Human-Human Dialogue Corpus

https://academiccommons.columbia.edu/catalog/ac:176612

- bAbi (Facebook Research)

https://research.fb.com/downloads/babi/

Machine reading

- bAbi QA (Facebook Research)

https://research.fb.com/downloads/babi/

- WikiReading (Google Research)

https://github.com/google-research-datasets/wiki-reading