Memory Networks for Language Understanding

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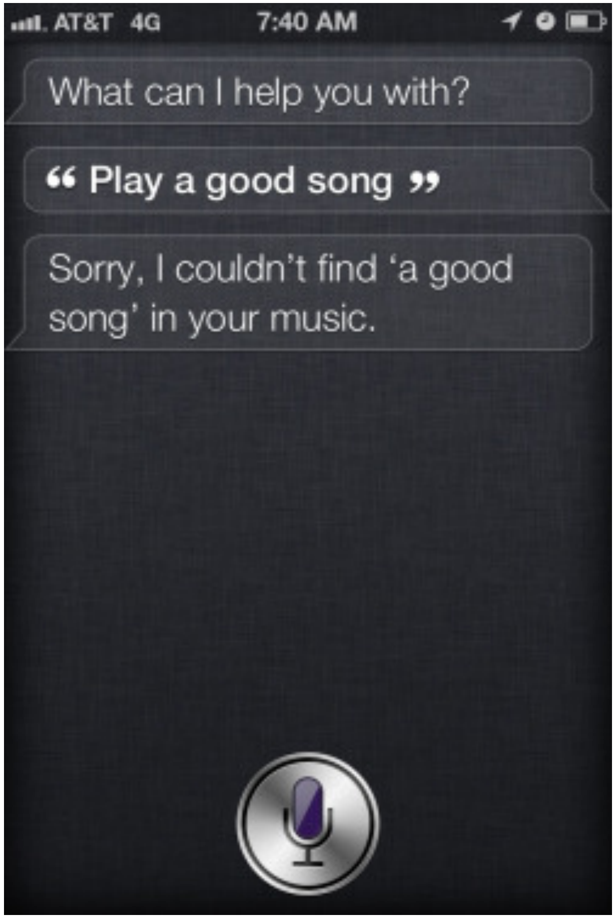
Facebook AI Research

Intelligent Conversational Agents



End-to-End Dialog Agents

While it is possible to build useful dialog agents as a set of separate black boxes with joining logic (*Google Now*, *Cortana*, *Siri*, *.. ?*) we believe a true dialog agent should:

- Be able to **combine all its knowledge** *to fulfill complex tasks*.
- **Handle long open-ended conversations** *involving effectively tracking many latent variables*.
- Be able to **learn** (new tasks) via conversation.

Our bet: **Machine Learning End-to-End systems** is the way forward in the long-run.

Memory Networks

- Class of models that combine large memory with learning component that can read and write to it.
- Incorporates **reasoning** with **attention** over **memory** (RAM).
- Most ML has limited memory which is more-or-less all that's needed for "low level" tasks e.g. object detection.

Our motivation: long-term memory is required to read a story and then e.g. answer questions about it.

Similarly, it's also required for **dialog**: to remember previous dialog (short- and long-term), and respond.

1. We first test this on the toy (bAbI) tasks.
2. Any interesting model has to be good on real data as well.

Memory Networks

Long-Term Memories	h_i	Shaolin Soccer directed_by Stephen Chow
		Shaolin Soccer written_by Stephen Chow
		Shaolin Soccer starred_actors Stephen Chow
		Shaolin Soccer release_year 2001
		Shaolin Soccer has_genre comedy
		Shaolin Soccer has_tags martial arts, kung fu soccer, stephen chow
		Kung Fu Hustle directed_by Stephen Chow
		Kung Fu Hustle written_by Stephen Chow
		Kung Fu Hustle starred_actors Stephen Chow
		Kung Fu Hustle has_genre comedy action
		Kung Fu Hustle has_imdb_votes famous
		Kung Fu Hustle has_tags comedy, action, martial arts, kung fu, china, soccer, hong kong, stephen chow
		The God of Cookery directed_by Stephen Chow
		The God of Cookery written_by Stephen Chow
		The God of Cookery starred_actors Stephen Chow
		The God of Cookery has_tags hong kong Stephen Chow
		From Beijing with Love directed_by Stephen Chow
		From Beijing with Love written_by Stephen Chow
		From Beijing with Love starred_actors Stephen Chow, Anita Yuen
		. . . <and more> . . .
Short-Term	c_1^u	1) I'm looking a fun comedy to watch tonight, any ideas?
Memories	c_1^r	2) Have you seen Shaolin Soccer? That was zany and great.. really funny but in a whacky way.
Input	c_2^u	3) Yes! Shaolin Soccer and Kung Fu Hustle are so good I really need to find some more Stephen Chow films I feel like there is more awesomeness out there that I haven't discovered yet ...
Output	y	4) God of Cookery is pretty great, one of his mid 90's hong kong martial art comedies.

Evaluating End-To-End Learners

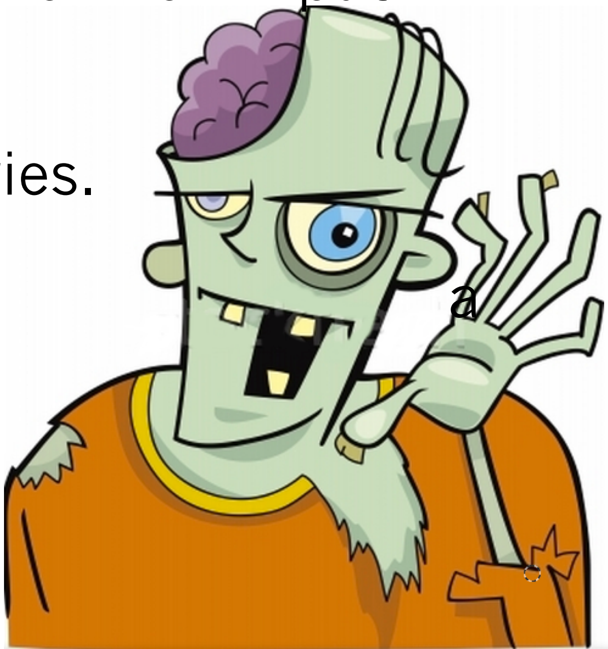
- Long Term goal: A learner can be trained (from scratch?) to understand and use language.
- Our main interest: uncover the learning algorithms able to do so.
- **Inspired by "A Roadmap towards Machine Intelligence" (Mikolov, Joulin, Baroni 2015)** we advocate a set of tasks to train & evaluate on:
  - Classic Language Modeling (Penn TreeBank, Text8)
  - Story understanding (Children's Book Test, News articles)
  - Open Question Answering (WebQuestions, WikiQA)
  - Goal-Oriented Dialog and Chit-Chat (Movie Dialog, Ubuntu)

What is a Memory Network?

Original paper description of class of models

MemNNs have four component networks (which may or may not have shared parameters):

- **I:** (input feature map) convert incoming data to the internal feature representation.
- **G:** (generalization) update memories given new input.
- **O:** produce new output (in feature representation space) given the memories.
- **R:** (response) convert output O into a response seen by the outside world.

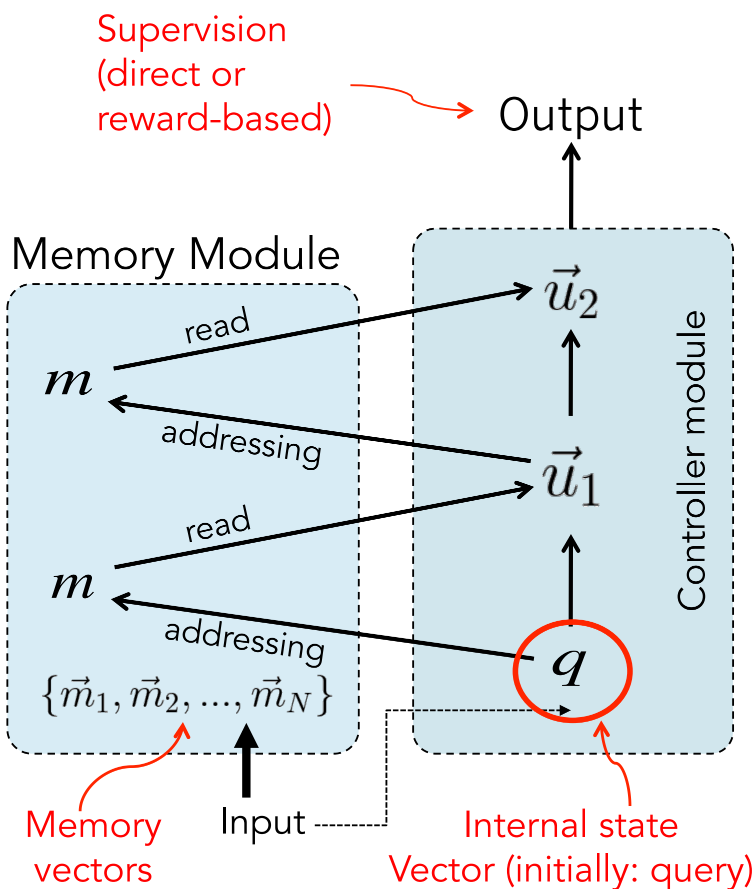


Some Memory Network-related Publications

- J. Weston, S. Chopra, A. Bordes. Memory Networks. ICLR 2015 (and arXiv:1410.3916).
- S. Sukhbaatar, A. Szlam, J. Weston, R. Fergus. End-To-End Memory Networks. NIPS 2015 (and arXiv:1503.08895).
- J. Weston, A. Bordes, S. Chopra, A. M. Rush, B. van Merriënboer, A. Joulin, T. Mikolov. Towards AI-Complete Question Answering: A Set of Prerequisite Toy Tasks. arXiv: 1502.05698.
- A. Bordes, N. Usunier, S. Chopra, J. Weston. Large-scale Simple Question Answering with Memory Networks. arXiv:1506.02075.
- J. Dodge, A. Gane, X. Zhang, A. Bordes, S. Chopra, A. Miller, A. Szlam, J. Weston. Evaluating Prerequisite Qualities for Learning End-to-End Dialog Systems. arXiv: 1511.06931.
- F. Hill, A. Bordes, S. Chopra, J. Weston. The Goldilocks Principle: Reading Children's Books with Explicit Memory Representations. arXiv:1511.02301.
- J. Weston. Dialog-based Language Learning. arXiv:1604.06045.
- A. Bordes, Jason Weston. Learning End-to-End Goal-Oriented Dialog. arXiv: 1605.07683.

Memory Network Models

implemented models..



[Figure by Saina Sukhbaatar]

Variants of the class...

Some options and extensions:

- **Representation of inputs and memories could use all kinds of encodings:** bag of words, RNN style reading at word or character level, etc.
- **Different possibilities for output module:** e.g. multi-class classifier or uses an RNN to output sentences.
- **If the memory is huge** (e.g. Wikipedia) we need to organize the memories. Solution: hash the memories to store in buckets (topics). Then, memory addressing and reading doesn't operate on *all* memories.
- **If the memory is full**, there could be a way of removing one it thinks is most useless; *i.e.* it ``forgets'' somehow. That would require a scoring function of the utility of each memory..

Task (1) Factoid QA with Single Supporting Fact (“where is actor”)

(Very Simple) Toy reading comprehension task:

John was in the bedroom.
Bob was in the office.
John went to kitchen. ← SUPPORTING FACT
Bob travelled back home.
Where is John? A:kitchen

(2) Factoid QA with Two Supporting Facts ("where is actor+object")

A harder (toy) task is to answer questions where two supporting statements have to be chained to answer the question:

John is in the playground.
Bob is in the office.
John picked up the football.
Bob went to the kitchen.
Where is the football? A:playground
Where was Bob before the kitchen? A:office

(2) Factoid QA with Two Supporting Facts ("where is actor+object")

A harder (toy) task is to answer questions where two supporting statements have to be chained to answer the question:

John is in the playground. ← SUPPORTING FACT
Bob is in the office.
John picked up the football. ← SUPPORTING FACT
Bob went to the kitchen.
Where is the football? A:playground
Where was Bob before the kitchen? A:office

To answer the first question *Where is the football?* both *John picked up the football* and *John is in the playground* are supporting facts.

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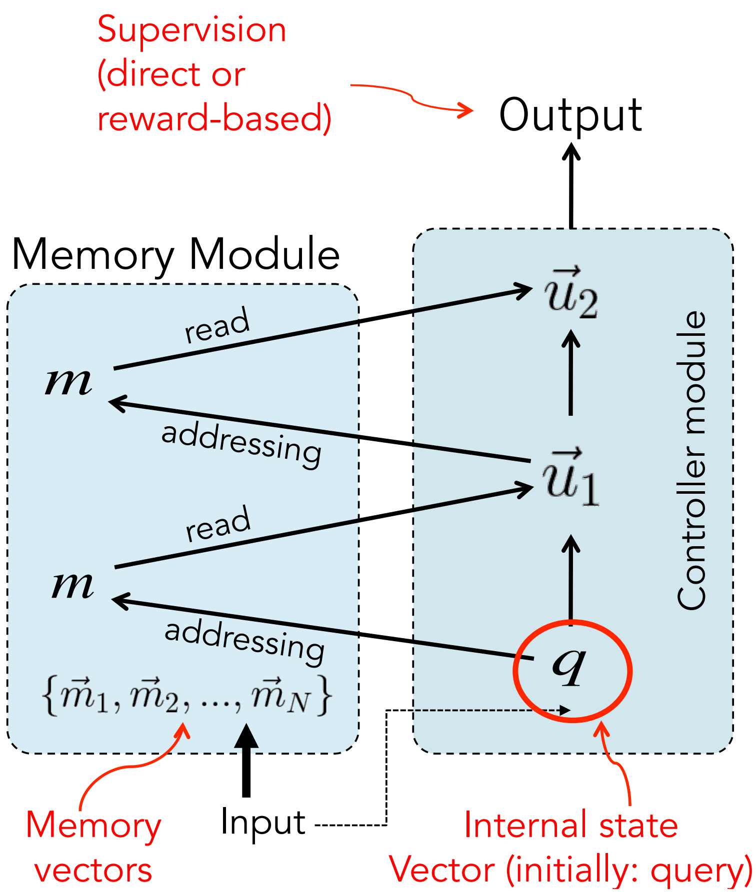
Memory Network Models

implemented models



[Figure by Saina Sukhbaatar]

The First **MemNN** Implemention

- I (input): converts to bag-of-word-embeddings x.
- G (generalization): stores x in next available slot m_N.
- O (output): Loops over all memories k=1 or 2 times:
  - 1st loop max: finds best match m_i with x.
  - 2nd loop max: finds best match m_J with (x, m_i).
  - The output o is represented with (x, m_i, m_J).
- R (response): ranks all words in the dictionary given o and returns best single word. *(OR: use a full RNN here)*

Matching function

- For a given Q, we want a good match to the relevant memory slot(s) containing the answer, e.g.:

Match(Where is the football ?, John picked up the football)

- We use a $q^T U^T U d$ embedding model with word embedding features:
  - *LHS features:* Q:Where Q:is Q:the Q:football Q:?
  - *RHS features:* D:John D:picked D:up D:the D:football QDMatch:the QDMatch:football

(QDMatch:football is a feature to say there's a Q&A word match, which can help.)

The parameters U are trained with a margin ranking loss: supporting facts should score higher than non-supporting facts.

Matching function: 2nd hop

- On the 2nd hop we match question & 1st hop to new fact:

Match([Where is the football ?, John picked up the football], John is in the playground)

- We use the same $q^T U^T U d$ embedding model:
  - *LHS features:* Q:Where Q:is Q:the Q:football Q:? Q2: John Q2:picked Q2:up Q2:the Q2:football
  - *RHS features:* D:John D:is D:in D:the D:playground QDMatch:the QDMatch:is .. Q2DMatch:John

Objective function

Minimize:

$$\sum_{\bar{f} \neq \mathbf{m}_{o_1}} \max(0, \gamma - s_O(x, \mathbf{m}_{o_1}) + s_O(x, \bar{f})) +$$

$$\sum_{\bar{f}' \neq \mathbf{m}_{o_2}} \max(0, \gamma - s_O([x, \mathbf{m}_{o_1}], \mathbf{m}_{o_2}]) + s_O([x, \mathbf{m}_{o_1}], \bar{f}'])) +$$

$$\sum_{\bar{r} \neq r} \max(0, \gamma - s_R([x, \mathbf{m}_{o_1}, \mathbf{m}_{o_2}], r) + s_R([x, \mathbf{m}_{o_1}, \mathbf{m}_{o_2}], \bar{r}]))$$

Where: S_O is the matching function for the Output component.
S_R is the matching function for the Response component.
x is the input question.
m_{O1} is the first true supporting memory (fact).
m_{O2} is the first second supporting memory (fact).
r is the response
True facts and responses $m_{O1,}$ m_{O2} and r should have higher scores than all other facts and responses by a given margin.

Comparing triples

- We also need time information for the bAbI tasks. We tried adding absolute time as a feature: it works, but the following idea can be better:
- Seems to work better if we compare triples:
- Match(Q,D,D’) returns < 0 if D is better than D’

  returns > 0 if D’ is better than D

We can loop through memories, keep best m_i at each step.

Now the features include *relative* time features:

L.H.S: same as before

R.H.S: features(D) DbeforeQ:*0-or-1*

-features(D’) D’beforeQ:*0-or-1* DbeforeD’:*0-or-1*

Comparing triples: Objective and Inference

$$\sum_{\bar{f} \neq \mathbf{m}_{o_1}} \max(0, \gamma - s_{O_t}(x, \mathbf{m}_{o_1}, \bar{f})) + \sum_{\bar{f} \neq \mathbf{m}_{o_1}} \max(0, \gamma + s_{O_t}(x, \bar{f}, \mathbf{m}_{o_1})) +$$
$$\sum_{\bar{f}' \neq \mathbf{m}_{o_2}} \max(0, \gamma - s_{O_t}([x, \mathbf{m}_{o_1}], \mathbf{m}_{o_2}, \bar{f}')) + \sum_{\bar{f}' \neq \mathbf{m}_{o_2}} \max(0, \gamma + s_{O_t}([x, \mathbf{m}_{o_1}], \bar{f}', \mathbf{m}_{o_2}) +$$
$$\sum_{\bar{r} \neq r} \max(0, \gamma - s_R([x, \mathbf{m}_{o_1}, \mathbf{m}_{o_2}], r) + s_R([x, \mathbf{m}_{o_1}, \mathbf{m}_{o_2}], \bar{r}]))$$

Similar to before, except now for both m_{o1} and m_{o2} we need to have two terms considering them as the second or third argument to the S_{Ot} as they may appear on either side during inference:

Algorithm 1 O_t replacement to arg max when using write time features

```
function O_t(q, m)
    t ← 1
    for i = 2, ..., N do
        if s_{O_t}(q, m_i, m_t) > 0 then
            t ← i
        end if
    end for
    return t
end function
```

bAbI Experiment 1

- 10k sentences. (Actor: only ask questions about actors.)
- Difficulty: how many sentences in the past when entity mentioned.
- Fully supervised (supporting sentences are labeled).
- Compare RNN (no supervision)
  and MemNN hops *k = 1 or 2*, & with/without time features.

	Difficulty 1		Difficulty 5	
Method	actor	actor+object	actor	actor+object
RNN	0%	42%	71%	83%
MemNN $k = 1$	10%	81%	54%	79%
MemNN $k = 1$ (+time)	0%	27%	0%	27%
MemNN $k = 2$ (+time)	0%	0.05%	0%	0.6%

Difficulty 5 -- Max mem. sz. required: 65   Average mem. sz. required: 9

bAbI Experiment 1

- Example test story + predictions:

Antoine went to the kitchen. Antoine got the milk. Antoine travelled to the office. Antoine dropped the milk. Sumit picked up the football. Antoine went to the bathroom. Sumit moved to the kitchen.

- *where is the milk now?* A: office
- *where is the football?* A: kitchen
- *where is Antoine ?* A: bathroom
- *where is Sumit ?* A: kitchen
- *where was Antoine before the bathroom*? A: office

Unsegmented setup; R module is an RNN

Joe went to the garden then Fred picked up the milk; Joe moved to the bathroom and Fred dropped the milk, and then Dan moved to the living room.

- *Where is Dan?* A: living room I believe
- *Where is Joe?* A: the bathroom

Fred moved to the bedroom and Joe went to the kitchen then Joe took the milk there and Dan journeyed to the bedroom; Joe discarded the milk.

- *Where is the milk now?* A: the milk is in the kitchen
- *Where is Dan now?* A: I think he is in the bedroom

Joe took the milk there, after that Mike travelled to the office, then Joe went to the living room, next Dan went back to the kitchen and Joe travelled to the office.

- *Where is Joe now?* A: I think Joe is in the office

Larger QA: Reverb Dataset in (Fader et al., 13)

- 14M statements, stored as (subject, relation, object) triples. Triples are REVERB extractions mined from ClueWeb09.
- Statements cover diverse topics:
  - (milne, authored, winnie-the-pooh)
  - (sheep, be-afraid-of, wolf), *etc...*
- Weakly labeled QA pairs and 35M paraphrased questions from WikiAnswers:
  - ``Who wrote the Winnie the Pooh books?
  - ``Who is poohs creator?''

Results: QA on Reverb data from (Fader et al.)

- 14M statements stored in the memNN memory.
- *k=1 loops* MemNN, *128-dim* embedding.
- R response simply outputs top scoring statement.
- Time features are not necessary, hence not used.
- We also tried adding bag of words (BoW) features.

Method	F1
(Fader et al., 2013)	0.54
(Bordes et al., 2014)	0.73
MemNN	0.72
MemNN (with BoW features)	0.82

Fast QA on Reverb data

Scoring all 14M candidates in the memory is slow.

We consider speedups using hashing in S and O as mentioned earlier:

- Hashing via words (*essentially: inverted index*)
- Hashing via k-means in embedding space (k=1000)

Method	Embedding	Embed+BoW	candidates
MemNN (no hashing)	0.72	0.82	14M
MemNN (word hash)	0.63	0.68	13k (1000x)
MemNN (clust hash)	0.71	0.80	177k (80x)

A MemNN multitasked on bAbI data and Reverb QA data

The "story" told to the model *after* training:

Antoine went to the kitchen. Antoine picked up the milk. Antoine travelled to the office.

MemNN's answers to some questions:

- *Where is the milk?* A: office
- *Where was Antoine before the office?* A: kitchen
- *Where does milk come from?* A: milk come from cow
- *What is a cow a type of?* A: cow be female of cattle
- *Where are cattle found?* A: cattle farm become widespread in brazil
- *What does milk taste like?* A: milk taste like milk
- *What does milk go well with?* A: milk go with coffee

Related Memory Models

(published before or ~same time as original paper)

- RNNSearch (Bahdanau et al.) for Machine Translation
  - Can be seen as a Memory Network where memory goes back only one sentence (writes embedding for each word).
  - At prediction time, reads memory and performs a soft max to find best alignment (most useful words). 1 hop only.
- Generating Sequences With RNNs (Graves, '13)
  - Also does alignment with previous sentence to generate handwriting (so RNN knows what letter it's currently on).
- Neural Turing Machines (Graves et al., 14)
  [on arxiv just 5 days after MemNNs!]
  - Has read and write operations over memory to perform tasks (e.g. copy, sort, associative recall).
  - 128 memory slots in experiments; content addressing computes a score for each slot ➔ slow for large memory?
- Earlier work by (Das '92), (Schmidhuber et al., 93), DISCERN (Miikkulainen, '90) and others...

Learning of Basic Algorithms using Reasoning, Attention, Memory (RAM) (e.g. addition, multiplication, sorting)

Methods include adding stacks and addressable memory to RNNs:

- **"Neural Net Architectures for Temporal Sequence Processing."** M. Mozer
- **"Neural Turing Machines"** A. Graves, G. Wayne, I. Danihelka.
- **"Inferring Algorithmic Patterns with Stack Augmented Recurrent Nets."** A. Joulin, T. Mikolov.
- **"Learning to Transduce with Unbounded Memory"** E. Grefenstette et al.
- **"Neural Programmer-Interpreters"** S. Reed, N. de Freitas.
- **"Reinforcement Learning Turing Machine."** W. Zaremba and I. Sutskever.
- **"Learning Simple Algorithms from Examples"** W. Zaremba, T. Mikolov, A. Joulin, R. Fergus.
- **"The Neural GPU and the Neural RAM machine"** I. Sutskever.

Classic NLP tasks for RAM

Classic Language Modeling:

- **"Long short-term memory"** Sepp Hochreiter, Jürgen Schmidhuber.

Machine translation:

- **"Sequence to Sequence Learning with Neural Networks"** I. Sutskever, O. Vinyals, Q. Le.
- **"Neural Machine Translation by Jointly Learning to Align and Translate"** D. Bahdanau, K. Cho, Y. Bengio.

Parsing:

- **"Grammar as a Foreign Language"** O. Vinyals, L. Kaiser, T. Koo, S. Petrov, I. Sutskever, G. Hinton.

Entailment:

- **"Reasoning about Entailment with Neural Attention"** T. Rocktäschel, E. Grefenstette, K. Hermann, T. Kočiský, P. Blunsom.

Summarization:

- **"A Neural Attention Model for Abstractive Sentence Summarization"** A. M. Rush, S. Chopra, J. Weston.

Reasoning with synthetic language

- **"A Roadmap towards Machine Intelligence"** T. Mikolov, A. Joulin, M. Baroni.
- **"Towards AI-Complete Question Answering: A Set of Prerequisite Toy Tasks"** J. Weston, A. Bordes, S. Chopra, A.. Rush, B. van Merriënboer, A. Joulin, T. Mikolov.

Several new models that attempt to solve bAbI tasks:

- **"Dynamic Memory Networks for Natural Language Processing"** A. Kumar, O. Irsoy, P. Ondruska, M. Iyyer, J. Bradbury, I. Gulrajani, R. Socher.
- **"Towards Neural Network-based Reasoning"** B. Peng, Z. Lu, H. Li, K. Wong.
- **"End-To-End Memory Networks"** S. Sukhbaatar, A. Szlam, J. Weston, R. Fergus.

New NLP Datasets for RAM

Understanding news articles:

- **"Teaching Machines to Read and Comprehend"** K. Hermann, T. Kočiský, E. Grefenstette, L. Espeholt, W. Kay, M. Suleyman, P. Blunsom.

Understanding children's books:

- **"The Goldilocks Principle: Reading Children's Books with Explicit Memory Representations"** F. Hill, A. Bordes, S. Chopra, J. Weston.

Conducting Dialog:

- **"Hierarchical Neural Network Generative Models for Movie Dialogues"** I. Serban, A. Sordoni, Y. Bengio, A. Courville, J. Pineau.
- **"A Neural Network Approach to Context-Sensitive Generation of Conversational Responses"** Sordoni et al.
- **"Neural Responding Machine for Short-Text Conversation"** L. Shang, Z. Lu, H.Li.
- **"Evaluating Prerequisite Qualities for Learning End-to-End Dialog Systems"** J. Dodge, A. Gane, X. Zhang, A. Bordes, S. Chopra, A. Miller, A. Szlam, J. Weston.

General Question Answering:

- **"Large-scale Simple Question Answering with Memory Networks"** A. Bordes, N. Usunier, S. Chopra, J. Weston.

What was next for MemNNs?

- Make the language much harder: coreference, conjunctions, negations, etc. etc – *will it work?*
- MemNNs that reason with *more than* 2 supporting memories.
- End-to-end? (doesn’t need supporting facts)
- More useful applications on real datasets.
- Dialog: Ask questions? Say statements?
- *Do MemNN ideas extend to other ML tasks and model variants, .e.g. visual QA, perform actions…? [A: yes!].*

bAbI tasks: what reasoning tasks would we like models to work on?

- We define 20 tasks (generated by the simulation) that we can test new models on. (See: http://fb.ai/babi)
- The idea is they are a bit like software tests: each task checks if an ML system has a certain skill.
- We would like each "skill" we check to be a natural task for humans w.r.t. text understanding & reasoning, humans should be able to get 100%.

J. Weston, A. Bordes, S. Chopra, T. Mikolov. Towards AI-Complete Question Answering: A Set of Prerequisite Toy Tasks. arXiv:1502.05698.

Simulation commands

- go <place>
- get <object>
- get <object1> from <object2>
- put <object1> in/on <object2>
- give <object> to <person>
- drop <object>
- look
- inventory
- examine <object>

+ 2 commands for "gods" (superusers):

- create <object>
- set <obj1> <relation> <obj2>

Example

Simple grammar

Command format

```
jason go kitchen
jason get milk
jason go office
jason drop milk
jason go bathroom
where is milk ?   A: office
where is jason? A: bathroom
```

Story

Jason went to the kitchen.

Jason picked up the milk.

Jason travelled to the office.

Jason left the milk there.

Jason went to the bathroom.

Where is the milk now? A: office

Where is Jason? A: bathroom

Task (1) Factoid QA with Single Supporting Fact ("where is actor")

Our first task consists of questions where a single supporting fact, previously given, provides the answer.

We test simplest case of this, by asking for the location of a person.

A small sample of the task is thus:

John is in the playground. ← SUPPORTING FACT
Bob is in the office.
Where is John? A:playground

We could use supporting facts for supervision at training time, but are not known at test time (we call this "strong supervision"). However weak supervision is much better!!

(2) Factoid QA with Two Supporting Facts ("where is actor+object")

A harder task is to answer questions where two supporting statements have to be chained to answer the question:

John is in the playground. ← SUPPORTING FACT
Bob is in the office.
John picked up the football. ← SUPPORTING FACT
Bob went to the kitchen.
Where is the football? A:playground

To answer the question *Where is the football?* both *John picked up the football* and *John is in the playground* are supporting facts.

.

(3) Factoid QA with Three Supporting Facts

Similarly, one can make a task with three supporting facts:

John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A:office

The first three statements are all required to answer this.

(4) Two Argument Relations: Subject vs. Object

To answer questions the ability to differentiate and recognize subjects and objects is crucial.

We consider the extreme case: sentences feature re-ordered words:

The office is north of the bedroom.
The bedroom is north of the bathroom.
What is north of the bedroom? A:office
What is the bedroom north of? A:bathroom

Note that the two questions above have exactly the same words, but in a different order, and different answers.

So a bag-of-words will not work.

(6) Yes/No Questions

- This task tests, in the simplest case possible (with a single supporting fact) the ability of a model to answer true/false type questions:

John is in the playground.
Daniel picks up the milk.
Is John in the classroom? A:no
Does Daniel have the milk? A:yes

(7) Counting

Tests ability to count sets:

Daniel picked up the football.
Daniel dropped the football.
Daniel got the milk.
Daniel took the apple.
How many objects is Daniel holding? A:two

(8) Lists/Sets

- Tests ability to produce lists/sets:

Daniel picks up the football.
Daniel drops the newspaper.
Daniel picks up the milk.
What is Daniel holding? A:milk,football

(11) Basic Coreference (nearest referent)

Daniel was in the kitchen.
Then he went to the studio.
Sandra was in the office.
Where is Daniel? A:studio

(13) Compound Coreference

Daniel and Sandra journeyed to the office.
Then they went to the garden.
Sandra and John travelled to the kitchen.
After that they moved to the hallway.
Where is Daniel? A:garden

(14) Time manipulation

- While our tasks so far have included time implicitly in the *order* of the statements, this task tests understanding the use of time expressions within the statements:

In the afternoon Julie went to the park.
Yesterday Julie was at school.
Julie went to the cinema this evening.
Where did Julie go after the park? A:cinema

Much harder difficulty: adapt a real time expression labeling dataset into a question answer format, e.g. Uzzaman et al., '12.

(15) Basic Deduction

- This task tests basic deduction via inheritance of properties:

Sheep are afraid of wolves.
Cats are afraid of dogs.
Mice are afraid of cats.
Gertrude is a sheep.
What is Gertrude afraid of? A:wolves

Deduction should prove difficult for MemNNs because it effectively involves search, although our setup might be simple enough for it.

(17) Positional Reasoning

- This task tests spatial reasoning, one of many components of the classical SHRDLU system:

The triangle is to the right of the blue square.
The red square is on top of the blue square.
The red sphere is to the right of the blue square.
Is the red sphere to the right of the blue square? A:yes
Is the red square to the left of the triangle? A:yes

(18) Reasoning about size

- This tasks requires reasoning about relative size of objects and is inspired by the commonsense reasoning examples in the Winograd schema challenge:

The football fits in the suitcase. The suitcase fits in the cupboard. The box of chocolates is smaller than the football. Will the box of chocolates fit in the suitcase? A:yes

Tasks 3 (three supporting facts) and 6 (Yes/No) are prerequisites.

(19) Path Finding

- In this task the goal is to find the path between locations:

The kitchen is north of the hallway.
The den is east of the hallway.
How do you go from den to kitchen? A:west,north

This is going to prove difficult for MemNNs because it effectively involves search.

What models could we try?

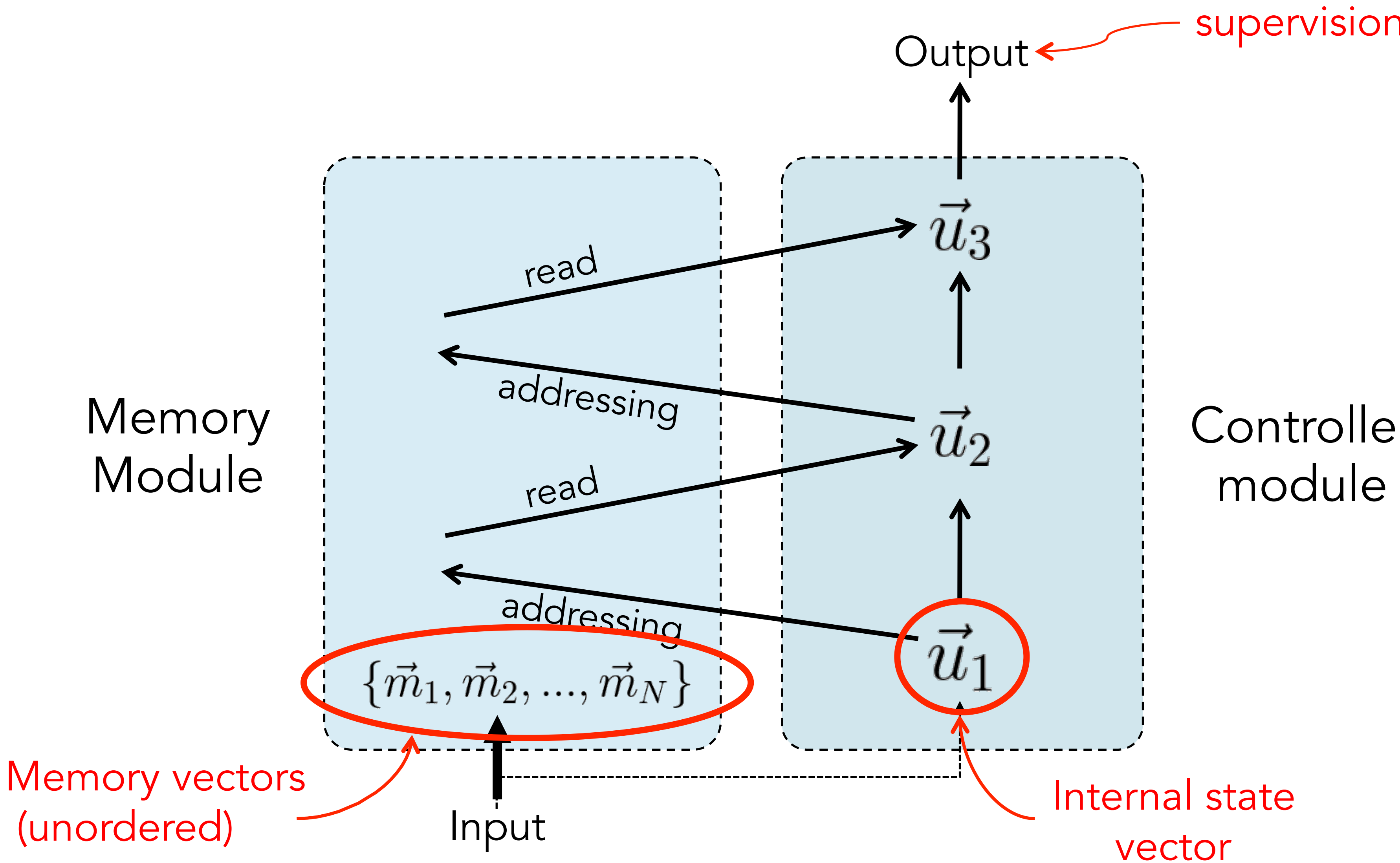
- Classic NLP cascade e.g. SVM-struct with bunch of features for subtasks: (*Not* End-to-End)
- N-gram models with SVM-type classifier?
- (LSTM) Recurrent Neural Nets?
- Memory Network variants … ?
- <Insert your new model here>

End-to-end Memory Network (MemN2N)

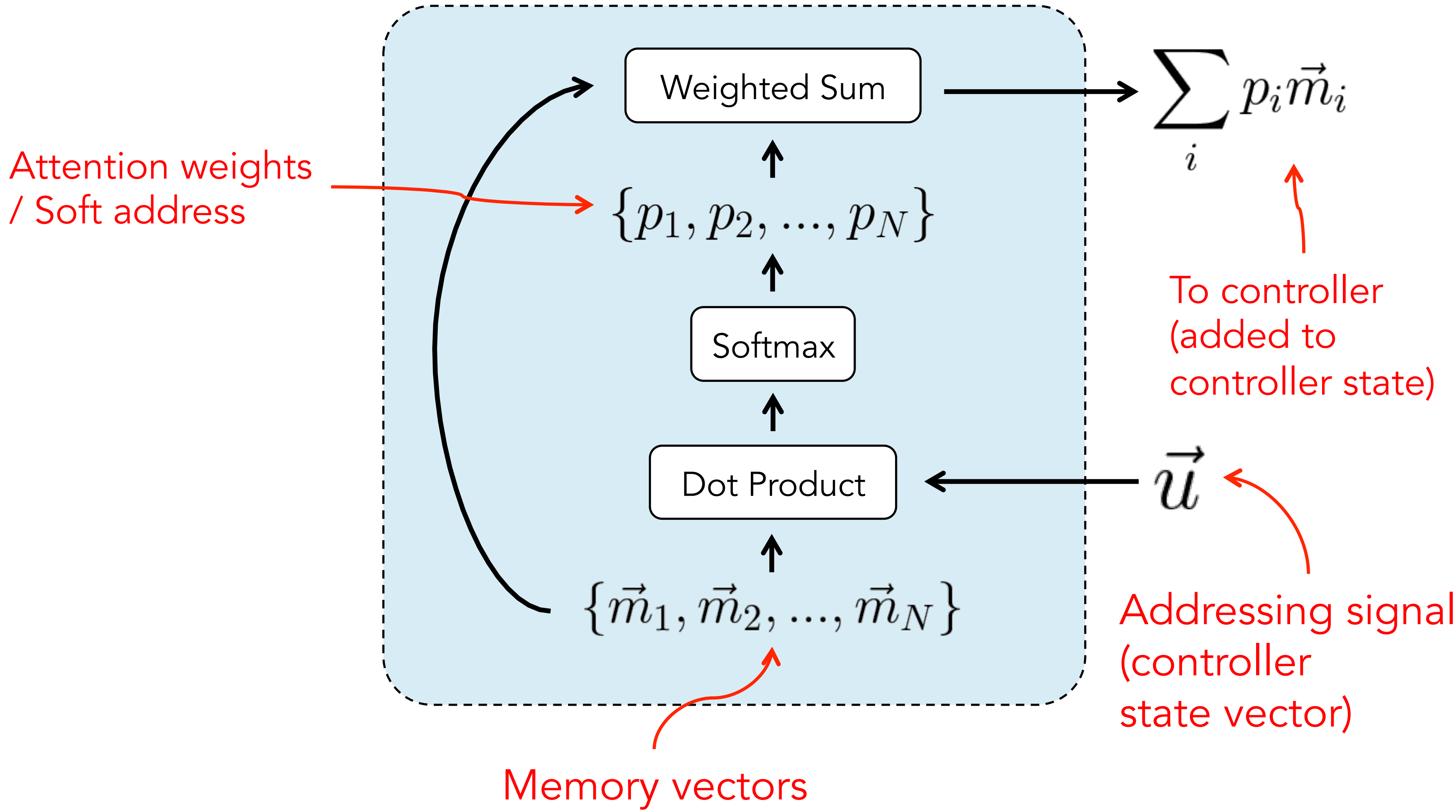
- New end-to-end (MemN2N) model (Sukhbaatar '15):
  - Reads from memory with **soft attention**
  - Performs **multiple lookups** (hops) on memory
  - End-to-end training with **backpropagation**
  - Only need supervision on the final output

- It is based on "Memory Networks" by [Weston, Chopra & Bordes ICLR 2015] but that had:
  - Hard attention
  - requires explicit supervision of attention during training
  - Only feasible for simple tasks

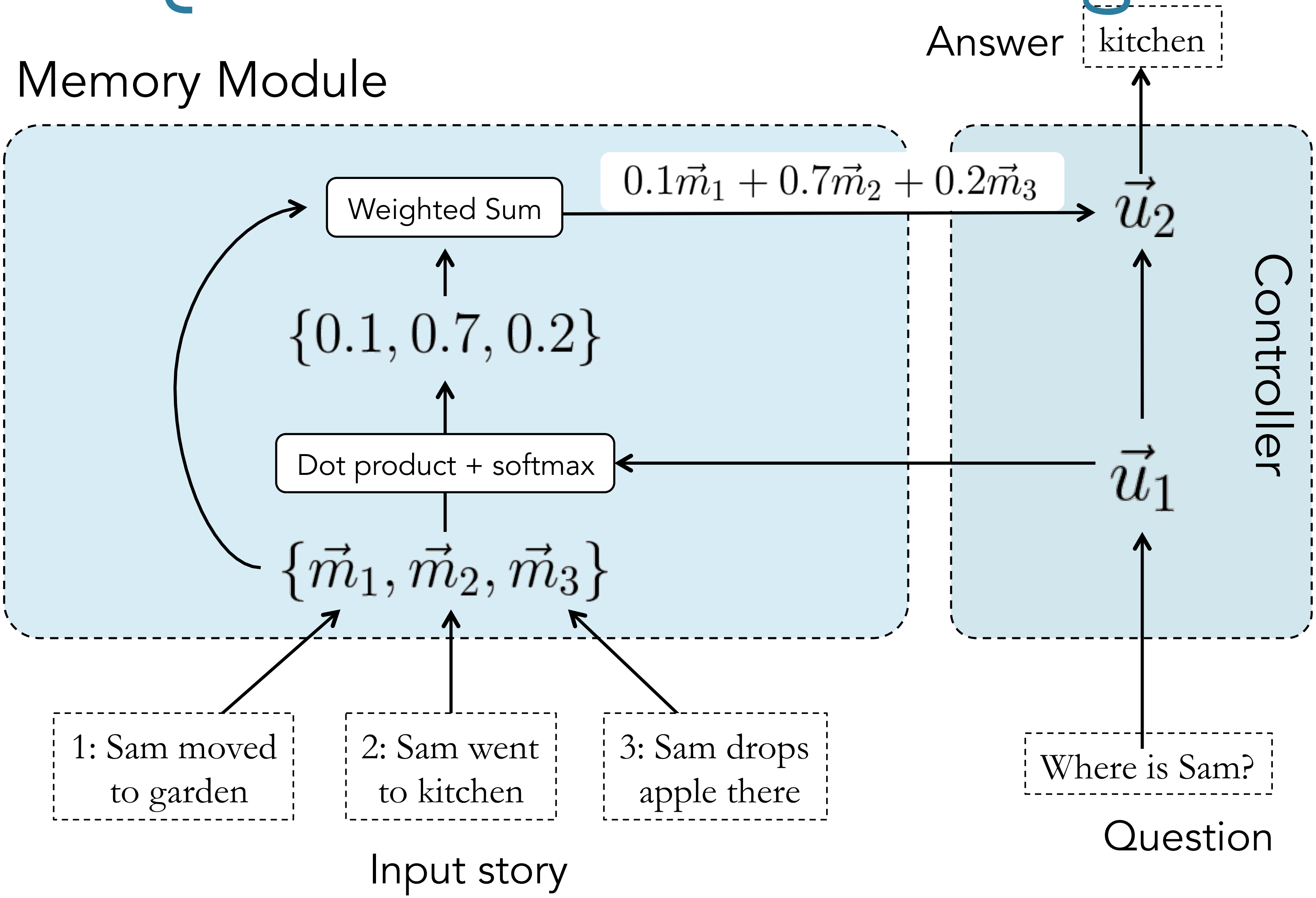
MemN2N architecture



Memory Module



Question & Answering



Memory Vectors

E.g.) constructing memory vectors with Bag-of-Words (BoW)

1. Embed each word
2. Sum embedding vectors

$$\text{"Sam drops apple"} \rightarrow \underbrace{\vec{v}_{\text{Sam}} + \vec{v}_{\text{drops}} + \vec{v}_{\text{apple}}}_{\text{Embedding Vectors}}$$

Positional Encoding of Words

Representation of inputs and memories could use all kinds of encodings: bag of words, RNN style reading at word or character level, etc.

We also built a positional encoding variant:
Words are represented by vectors as before. But instead of a bag, position is modeled by a multiplicative term on each word vector with weights depending on the position in the sentence.

Training on 1k stories

	Weakly supervised			Supervised Supp. Facts	
TASK	**N-grams**	**LSTMs**	**MemN2N**	**Memory Networks**	**StructSVM +coref+srl**
T1. Single supporting fact	36	50	PASS	PASS	PASS
T2. Two supporting facts	2	20	87	PASS	74
T3. Three supporting facts	7	20	60	PASS	17
T4. Two arguments relations	50	61	PASS	PASS	PASS
T5. Three arguments relations	20	70	87	PASS	83
T6. Yes/no questions	49	48	92	PASS	PASS
T7. Counting	52	49	83	85	69
T8. Sets	40	45	90	91	70
T9. Simple negation	62	64	87	PASS	PASS
T10. Indefinite knowledge	45	44	85	PASS	PASS
T11. Basic coreference	29	72	PASS	PASS	PASS
T12. Conjunction	9	74	PASS	PASS	PASS
T13. Compound coreference	26	PASS	PASS	PASS	PASS
T14. Time reasoning	19	27	PASS	PASS	PASS
T15. Basic deduction	20	21	PASS	PASS	PASS
T16. Basic induction	43	23	PASS	PASS	24
T17. Positional reasoning	46	51	49	65	61
T18. Size reasoning	52	52	89	PASS	62
T19. Path finding	0	8	7	36	49
T20. Agent's motivation	76	91	PASS	PASS	PASS

Attention during memory lookups

Samples from toy QA tasks

Story (1: 1 supporting fact)	Support	Hop 1	Hop 2	Hop 3
Daniel went to the bathroom.		0.00	0.00	0.03
Mary travelled to the hallway.		0.00	0.00	0.00
John went to the bedroom.		0.37	0.02	0.00
John travelled to the bathroom.	yes	0.60	0.98	0.96
Mary went to the office.		0.01	0.00	0.00
Where is John? Answer: bathroom Prediction: bathroom				

Story (2: 2 supporting facts)	Support	Hop 1	Hop 2	Hop 3
John dropped the milk.		0.06	0.00	0.00
John took the milk there.	yes	0.88	1.00	0.00
Sandra went back to the bathroom.		0.00	0.00	0.00
John moved to the hallway.	yes	0.00	0.00	1.00
Mary went back to the bedroom.		0.00	0.00	0.00
Where is the milk? Answer: hallway Prediction: hallway				

Story (16: basic induction)	Support	Hop 1	Hop 2	Hop 3
Brian is a frog.	yes	0.00	0.98	0.00
Lily is gray.		0.07	0.00	0.00
Brian is yellow.	yes	0.07	0.00	1.00
Julius is green.		0.06	0.00	0.00
Greg is a frog.	yes	0.76	0.02	0.00
What color is Greg? Answer: yellow Prediction: yellow				

Story (18: size reasoning)	Support	Hop 1	Hop 2	Hop 3
The suitcase is bigger than the chest.	yes	0.00	0.88	0.00
The box is bigger than the chocolate.		0.04	0.05	0.10
The chest is bigger than the chocolate.	yes	0.17	0.07	0.90
The chest fits inside the container.		0.00	0.00	0.00
The chest fits inside the box.		0.00	0.00	0.00
Does the suitcase fit in the chocolate? Answer: no Prediction: no				

20 bAbI Tasks

	Test Acc	Failed tasks
MemNN	93.3%	4
LSTM	49%	20
MemN2N 1 hop	74.82%	17
2 hops	84.4%	11
3 hops	87.6.%	11

So we still fail on some tasks....

.. and we could also make more tasks that we fail on!

Our hope is that a feedback loop of:

1. Developing **tasks** that **break models**, and
2. Developing **models** that can **solve tasks**

... leads in a **fruitful** research direction....

How about on real data?

- Toy AI tasks are important for developing innovative methods.
- But they do not give all the answers.

- How do these models work on real data?
  - Classic Language Modeling (Penn TreeBank, Text8)
  - Story understanding (Children's Book Test, News articles)
  - Open Question Answering (WebQuestions, WikiQA)
  - Goal-Oriented Dialog and Chit-Chat (Movie Dialog, Ubuntu)

Language Modeling

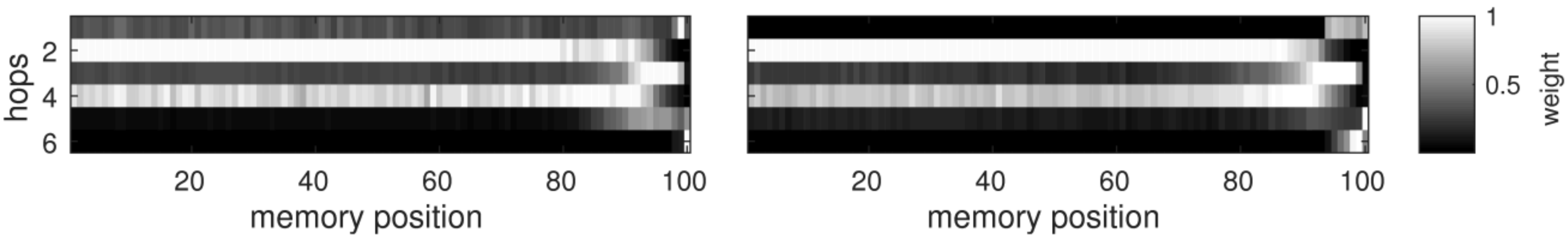
The goal is to predict the next word in a text sequence given the previous words. Results on the Penn Treebank and Text8 (Wikipedia-based) corpora.

	Penn Tree	Text8
RNN	129	184
LSTM	115	154
MemN2N 2 hops	121	187
5 hops	118	154
7 hops	111	147

Test perplexity

Hops vs. Attention:
Average over (PTB)

Average over (Text8)



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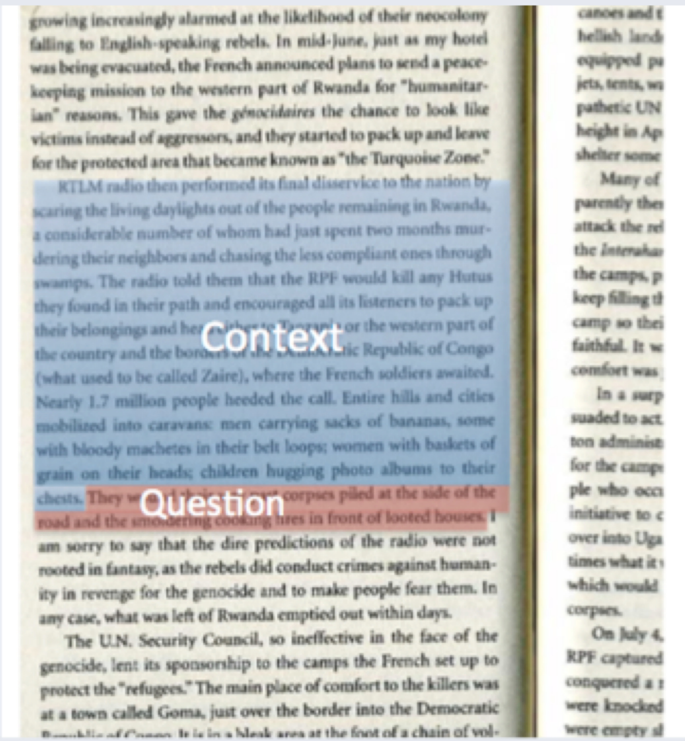
Test perplexity

MemNNs are in the same ballpark as LSTMs.

Hypothesis: many words (e.g. syntax words) don't actually need really long term context, and so memNNs don't help there.

Maybe MemNNs could eventually help more on things like nouns/entities?

Children books understanding



growing increasingly alarmed at the likelihood of their neocolony falling to English-speaking rebels. In mid-June, just as my hotel was being evacuated, the French announced plans to send a peace-keeping mission to the western part of Rwanda for "humanitarian" reasons. This gave the *génocidaires* the chance to look like victims instead of aggressors, and they started to pack up and leave for the protected area that became known as "the Turquoise Zone."

RTLM radio then performed its final disservice to the nation by scaring the living daylights out of the people remaining in Rwanda, a considerable number of whom had just spent two months murdering their neighbors and chasing the less compliant ones through swamps. The radio told them that the RPF would kill any Hutus they found in their path and encouraged all its listeners to pack up their belongings and he[illegible] or the western part of the country and the border[illegible] Republic of Congo (what used to be called Zaire), where the French soldiers awaited. Nearly 1.7 million people heeded the call. Entire hills and cities mobilized into caravans: men carrying sacks of bananas, some with bloody machetes in their belt loops; women with baskets of grain on their heads; children hugging photo albums to their chests. They [illegible] corpses piled at the side of the road and the smoldering cooking fires in front of looted houses. I am sorry to say that the dire predictions of the radio were not rooted in fantasy, as the rebels did conduct crimes against humanity in revenge for the genocide and to make people fear them. In any case, what was left of Rwanda emptied out within days.

The U.N. Security Council, so ineffective in the face of the genocide, lent its sponsorship to the camps the French set up to protect the "refugees." The main place of comfort to the killers was at a town called Goma, just over the border into the Democratic

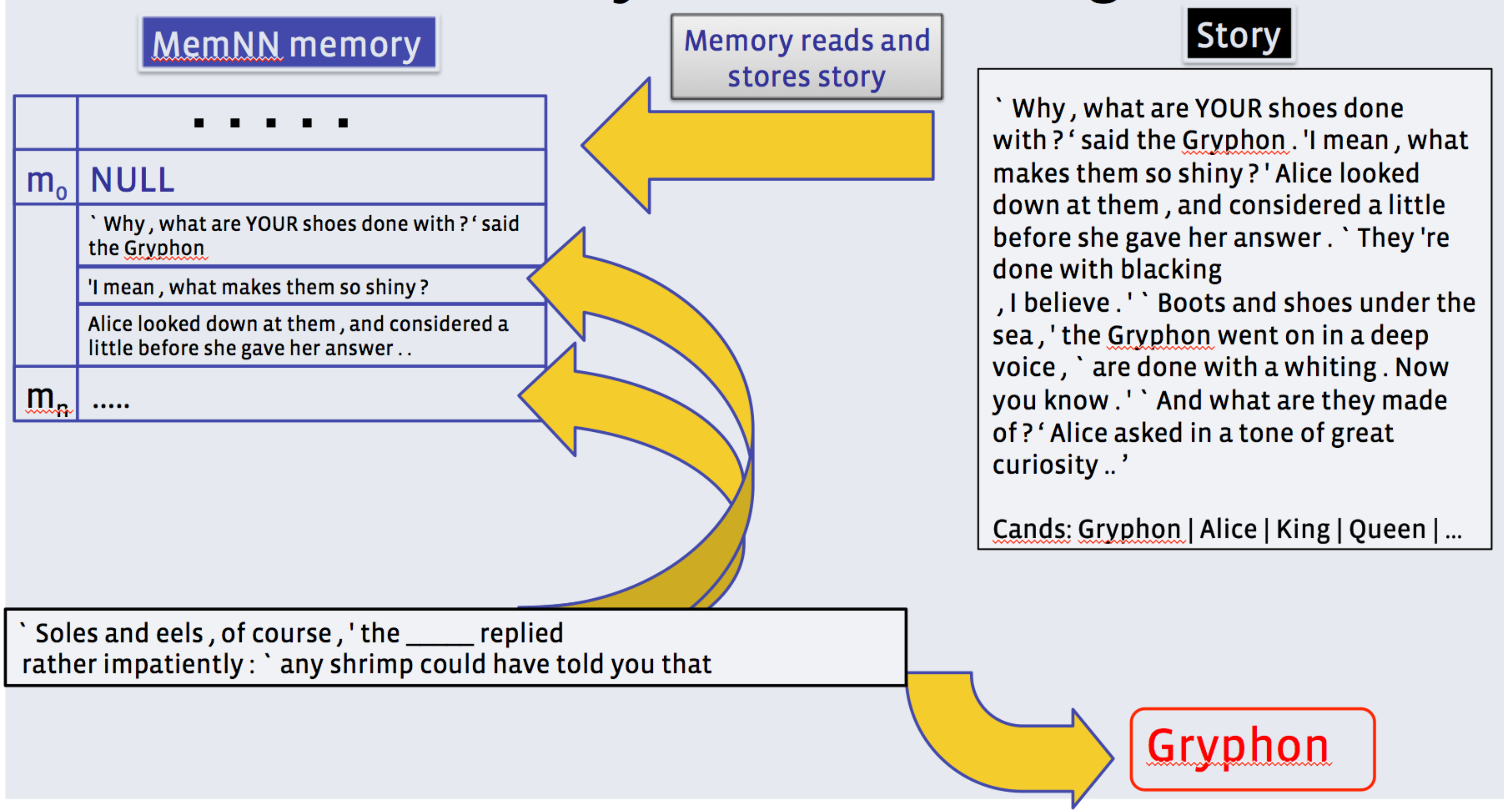
New dataset based on 118 children books from project Gutenberg

1 `` phebe beckoned to him ; i saw her , '' cried rose , staring hard at the door .
2 `` is it more presents coming ? ''
3 asked jamie , just as his brother re-appeared , looking more excited than ever .
4 `` yes ; a present for mother , and here it is ! ''
5 roared archie , flinging wide the door to let in a tall man , who cried out , `` where 's my little woman ?
6 the first kiss for her , then the rest may come on as fast as they like . ''
7 before the words were out of his mouth , mrs. jessie was half-hidden under his rough great-coat , and four boys were prancing about him clamouring for their turn .
8 of course , there was a joyful tumult for a time , during which rose slipped into the window recess and watched what went on , as if it were a chapter in a christmas story .
9 it was good to see bluff uncle jem look proudly at his tall son , and fondly hug the little ones .
10 it was better still to see him shake his brothers ' hands as if he would never leave off , and kiss all the sisters in a way that made even solemn aunt myra brighten up for a minute .

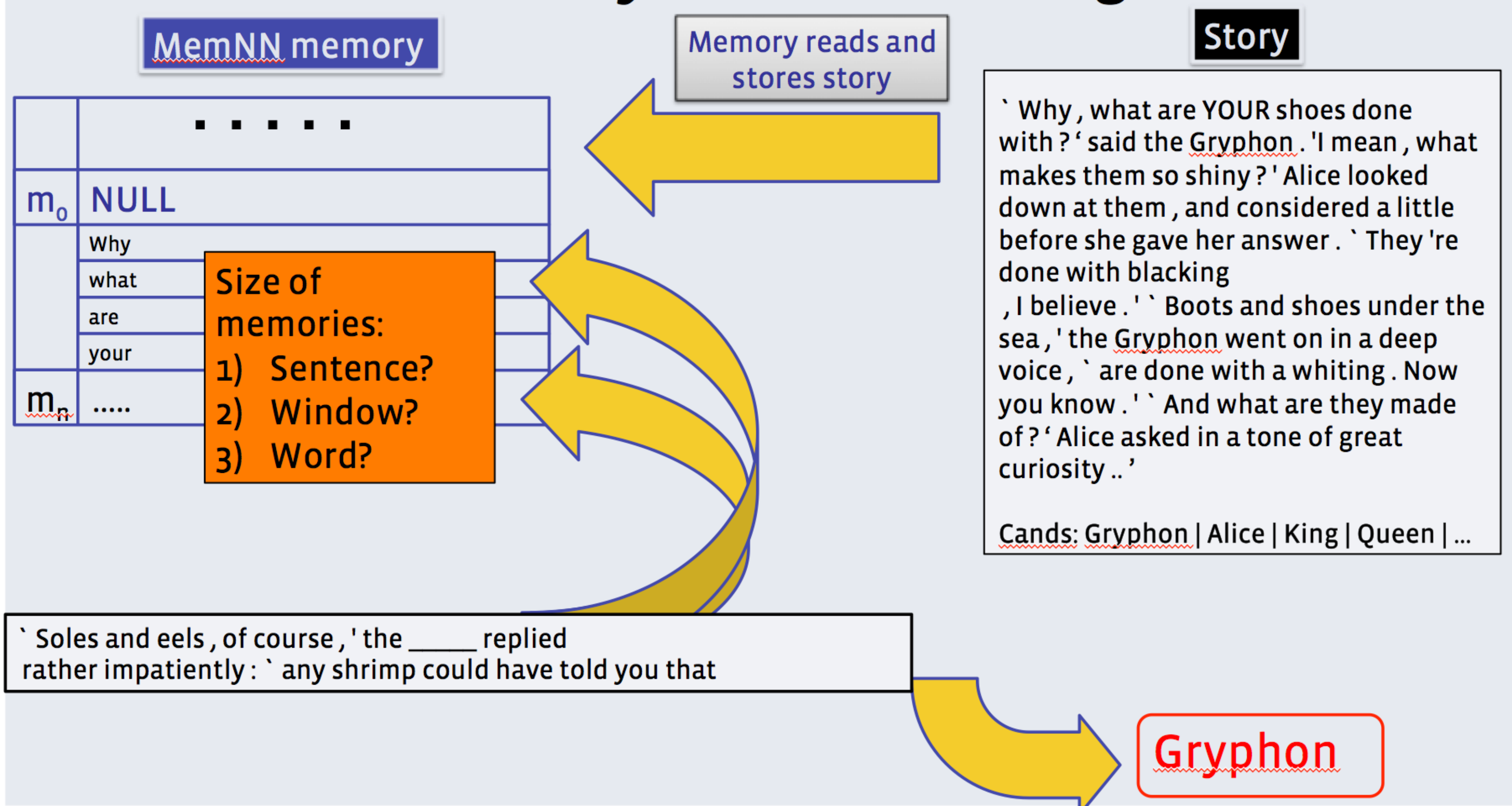
11 but it was best of all to see him finally established in grandfather 's chair , with his `` little woman '' beside him , his three youngest boys in his lap , and _____ hovering over him like a large-sized cherub .

faith | brothers | rose | <u>archie</u> | rest | mouth | way | mother | sisters | george

MemNNs for story understanding



MemNNs for story understanding



Self-Supervision Memory Network

Two tricks together that make things work a bit better:

1) Bypass module

Instead of the last output module being a linear layer from the output of the memory, assume the answer *is one of the memories.* Sum the scores of identical memories.

2) Self-Supervision

We know what the right answer is on the training data, so just directly train that memories containing the answer word to be supporting facts (have high probability).

Results on Children's Book Test

Methods	Named Entities	Common Nouns	Verbs	Prepositions
Humans (query)(*)	0.520	0.644	0.716	0.676
Humans (context+query)(*)	***0.816***	***0.816***	***0.828***	0.708
Maximum frequency (corpus)	0.120	0.158	0.373	0.315
Maximum frequency (context)	0.335	0.281	0.285	0.275
Sliding window	0.168	0.196	0.182	0.101
Word distance model	0.398	0.364	0.380	0.237
Kneser-Ney language model	0.390	0.544	0.778	0.768
Kneser-Ney language model + cache	0.439	0.577	0.772	0.679
Embedding Model (context+query)	0.253	0.259	0.421	0.315
Embedding Model (query)	0.351	0.400	0.614	0.535
Embedding Model (window)	0.362	0.415	0.637	0.589
Embedding Model (window+position)	0.402	0.506	0.736	0.670
LSTMs (query)	0.408	0.541	0.813	0.802
LSTMs (context+query)	0.418	0.560	**0.818**	0.791
Contextual LSTMs (window context)	0.436	0.582	0.805	**0.806**
MemNNs (lexical memory)	0.431	0.562	0.798	0.764
MemNNs (window memory)	0.493	0.554	0.692	0.674
MemNNs (sentential memory + PE)	0.318	0.305	0.502	0.326
MemNNs (window memory + self-sup.)	**0.666**	**0.630**	0.690	0.703

Question Answering on New's Articles

We evaluate our models on the data from:

"Teaching Machines to Read and Comprehend"

Karl Moritz Hermann, Tomáš Kočiský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, Phil Blunsom

	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 broad-caster 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*

Results on CNN QA dataset

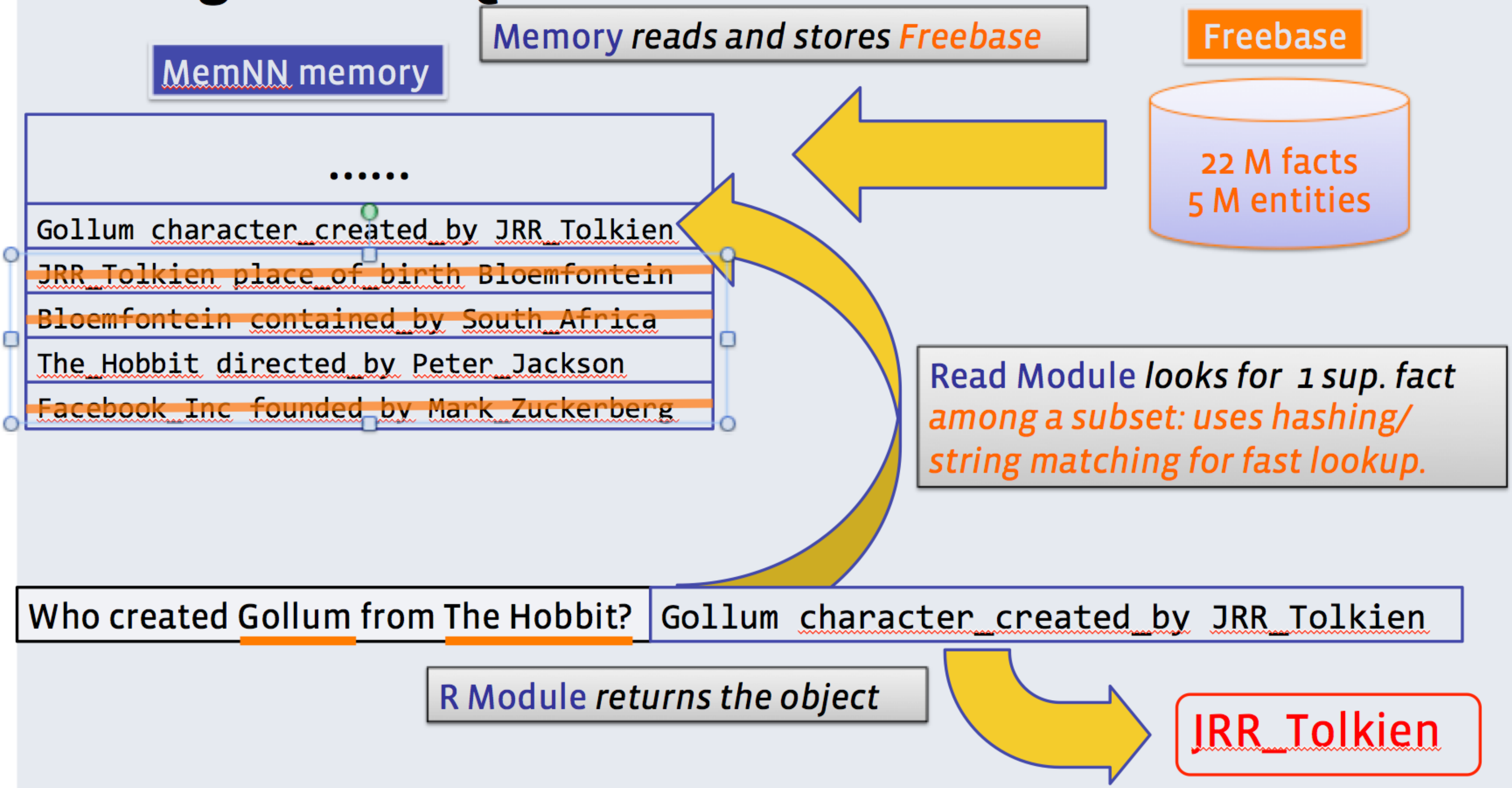
Methods	Validation	Test
Maximum frequency (article)$^{(*)}$	0.305	0.332
Sliding window	0.005	0.006
Word distance model$^{(*)}$	0.505	0.509
Deep LSTMs (article+query)$^{(*)}$	0.550	0.570
Contextual LSTMs ("Attentive reader")$^{(*)}$	0.616	0.630
Contextual LSTMs ("Impatient reader")$^{(*)}$	0.618	0.638
MemNNs (window memory)	0.580	0.606
MemNNs (window memory + self-sup.)	0.634	0.668
MemNNs (window memory + ensemble)	0.612	0.638
MemNNs (window memory + self-sup. + ensemble)	0.649	0.684
MemNNs (window + self-sup. + ensemble + exclud. coocurrences)	**0.662**	**0.694**

Table 3: **Results on CNN QA.** $^{(*)}$Results taken from Hermann et al. (2015).

Latest *Fresh* Results

- Our best results: QACNN: 69.4 CBT-NE: 66.6 CBT-V: 63.0
- Text Understanding with the Attention Sum Reader Network. Kadlec et al. (4 Mar '16) QACNN: 75.4 CBT-NE: 71.0 CBT-CN: 68.9
  Uses RNN style encoding of words + bypass module + 1 hop
- Iterative Alternating Neural Attention for Machine Reading. Sordoni et al. (7 Jun '16) QACNN: 76.1 CBT-NE: 72.0 CBT-CN: 71.0
- Natural Language Comprehension with the EpiReader. Trischler et al. (7 Jun '16) QACNN: 74.0 CBT-NE: 71.8 CBT-CN: 70.6
- Gated-Attention Readers for Text Comprehension. Dhingra et al. (5 Jun '16) QACNN: 77.4 CBT-NE: 71.9 CBT-CN: 69.
  Uses RNN style encoding of words + bypass module + multiplicative combination of query + multiple hops

Large Scale QA



WebQuestions & SimpleQuestions

- Decent results on WebQuestions, a popular QA task:

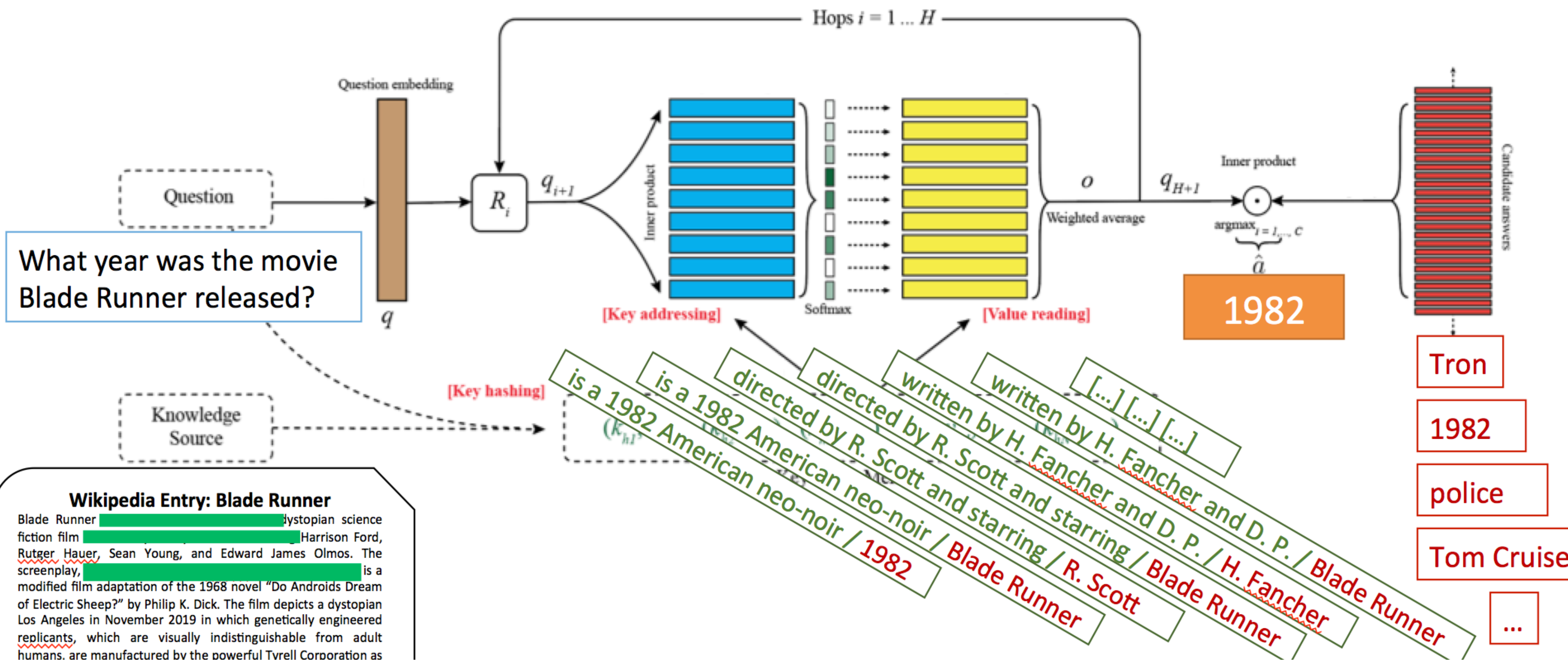
Random guess	1.9
(Bordes et al., 2014b)	29.7
(Berant et al., 2013)	31.3
(Bordes et al., 2014a)	39.2
(Berant and Liang, 2014)	39.9
(Yang et al., 2014)	41.3
MemNN	42.2

A. Bordes, N. Usunier, S. Chopra J.Weston. Large-scale Simple Question Answering with Memory Networks. arXiv:1506.02075.

- However now beaten by many results, especially (Yih et al. ACL '15) that achieves **52.5**! Several hand engineered features are used in that case. Note WebQuestions is very small (4k train+valid).

Recent Work: New Models for QA on documents

Miller et al. Key-Value Memory Networks for Directly Reading Documents. arXiv:1606.03126.



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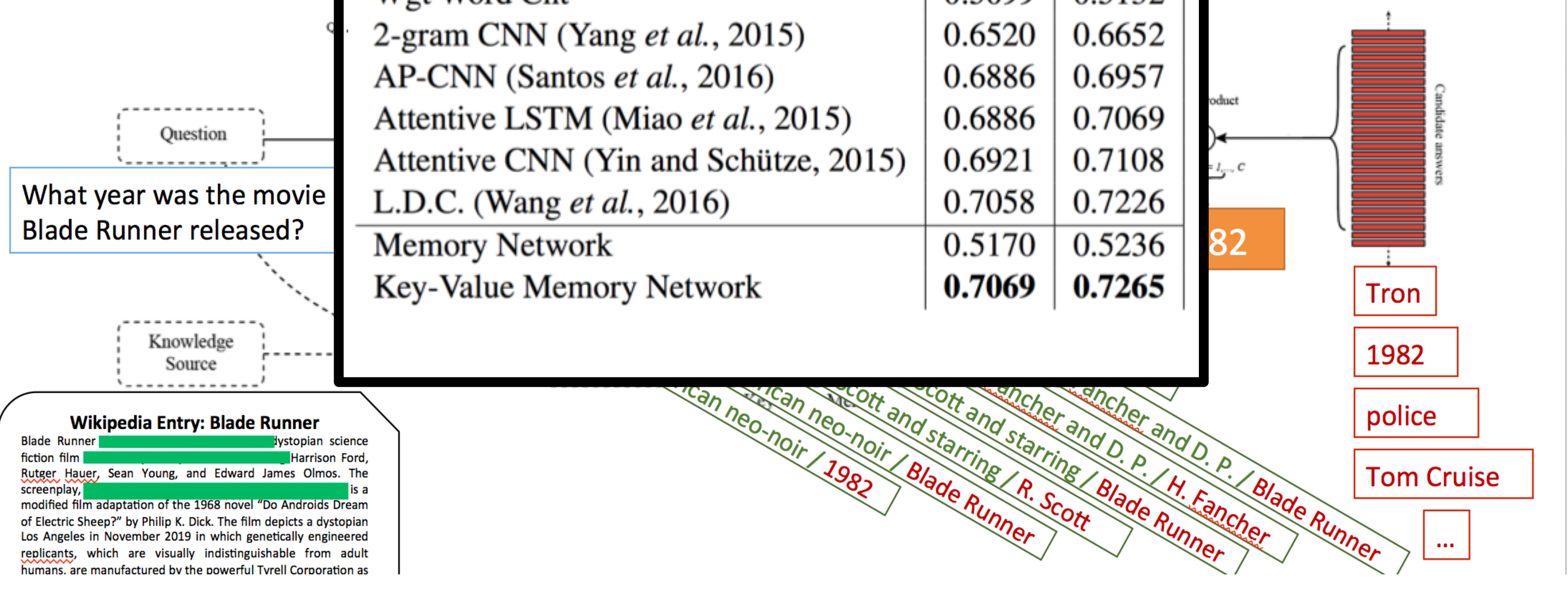
WikiQA Results

Method	MAP	MRR
Word Cnt	0.4891	0.4924
Wgt Word Cnt	0.5099	0.5132
2-gram CNN (Yang *et al.*, 2015)	0.6520	0.6652
AP-CNN (Santos *et al.*, 2016)	0.6886	0.6957
Attentive LSTM (Miao *et al.*, 2015)	0.6886	0.7069
Attentive CNN (Yin and Schütze, 2015)	0.6921	0.7108
L.D.C. (Wang *et al.*, 2016)	0.7058	0.7226
Memory Network	0.5170	0.5236
Key-Value Memory Network	**0.7069**	**0.7265**



How about on large scale dialog data? With multiple exchanges?

- Everything we showed so far was question answering potentially with long-term context.

- We have also built a Movie Dialog Dataset

  Closed, but large, domain about movies (75k entities, 3.5M ex).
  - Ask facts about movies?
  - Ask for opinions (recommendations) about movies?
  - Dialog combining facts and opinions?
  - General chit-chat about movies (statements not questions)?

And… combination of all above in one end-to-end model.

Recent Work: Combines QA with Dialog Tasks

Dodge et al. "Evaluating Prerequisite Qualities for Learning End-to-End Dialog Systems." ICLR '16

(Dialog 1) QA: *facts about movies*

Sample input contexts and target replies (in red) from Dialog Task 1:

What movies are about open source? Revolution OS
Ruggero Raimondi appears in which movies? Carmen
What movies did Darren McGavin star in? Billy Madison, The Night Stalker, Mrs. Pollifax-Spy, The Challenge
Can you name a film directed by Stuart Ortiz? Grave Encounters
Who directed the film White Elephant? Pablo Trapero
What is the genre of the film Dial M for Murder? Thriller, Crime
What language is Whity in? German

(Dialog 2) Recs: *movie recommendations*

Sample input contexts and target replies (in red) from Dialog Task 2:

Schindler's List, The Fugitive, Apocalypse Now, Pulp Fiction, and The Godfather are films I really liked. Can you suggest a film?
The Hunt for Red October

Some movies I like are Heat, Kids, Fight Club, Shaun of the Dead, The Avengers, Skyfall, and Jurassic Park. Can you suggest something else I might like? Ocean's Eleven

(Dialog 3) QA+Recs: *combination dialog*

Sample input contexts and target replies (in red) from Dialog Task 3:

I loved Billy Madison, Blades of Glory, Bio-Dome, Clue, and Happy Gilmore. I'm looking for a Music movie. School of Rock
What else is that about? Music, Musical, Jack Black, school, teacher, Richard Linklater, rock, guitar
I like rock and roll movies more. Do you know anything else?
Little Richard

(Dialog 4) Reddit: *real dialog*

Sample input contexts and target replies (in red) from Dialog Task 4:

I think the Terminator movies really suck, I mean the first one was kinda ok, but after that they got really cheesy. Even the second one which people somehow think is great. And after that... forgeddabotit.
C'mon the second one was still pretty cool.. Arny was still so badass, as was Sararah Connor's character.. and the way they blended real action and effects was perhaps the last of its kind...

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Memory Network: *example*

Memories	h_i	Shaolin Soccer written_by Stephen Chow
		Shaolin Soccer starred_actors Stephen Chow
		Shaolin Soccer release_year 2001
		Shaolin Soccer has_genre comedy
		Shaolin Soccer has_tags martial arts, kung fu soccer, stephen chow
		Kung Fu Hustle directed_by Stephen Chow
		Kung Fu Hustle written_by Stephen Chow
		Kung Fu Hustle starred_actors Stephen Chow
		Kung Fu Hustle has_genre comedy action
		Kung Fu Hustle has_imdb_votes famous
		Kung Fu Hustle has_tags comedy, action, martial arts, kung fu, china, soccer, hong kong, stephen chow
		The God of Cookery directed_by Stephen Chow
		The God of Cookery written_by Stephen Chow
		The God of Cookery starred_actors Stephen Chow
		The God of Cookery has_tags hong kong Stephen Chow
		From Beijing with Love directed_by Stephen Chow
		From Beijing with Love written_by Stephen Chow
		From Beijing with Love starred_actors Stephen Chow, Anita Yuen
		. . . <and more> . . .
Short-Term	c_1^u	1) I'm looking a fun comedy to watch tonight, any ideas?
Memories	c_1^r	2) Have you seen Shaolin Soccer? That was zany and great.. really funny but in a whacky way.
Input	c_2^u	3) Yes! Shaolin Soccer and Kung Fu Hustle are so good I really need to find some more Stephen Chow films I feel like there is more awesomeness out there that I haven't discovered yet ...

Results

Methods	QA Task (hits@1)	Recs Task (hits@100)	QA+Recs Task (hits@10)	Reddit Task (hits@10)
QA System (Bordes et al., 2014)	90.7	N/A	N/A	N/A
SVD	N/A	19.2	N/A	N/A
IR	N/A	N/A	N/A	23.7
LSTM	6.5	27.1	19.9	11.8
Supervised Embeddings	50.9	29.2	65.9	27.6
MemN2N	79.3	28.6	81.7	29.2
Joint Supervised Embeddings	43.6	28.1	58.9	14.5
Joint MemN2N	83.5	26.5	78.9	26.6

Ubuntu Data

Dialog dataset: Ubuntu IRC channel logs, users ask questions about issues they are having with Ubuntu and get answers by other users. (Lowe et al., '15)

Methods		Validation (hits@1)	Test (hits@1)
IR†		N/A	48.81
RNN†		N/A	37.91
LSTM†		N/A	55.22
MemN2N	1-hop	57.23	56.25
MemN2N	2-hops	64.28	63.51
MemN2N	3-hops	64.31	63.72
MemN2N	4-hops	64.01	62.82

Table 7: **Ubuntu Dialog Corpus results.** The evaluation is retrieval-based, similar to that of Reddit (Task 4). For each dialog, the correct answer is mixed among 10 random candidates; Hits@1 (in %) are reported. Methods with † have been ran by Lowe et al. (2015).

Best results currently reported:
Sentence Pair Scoring: Towards Unified Framework for Text Comprehension
Petr Baudiš, Jan Pichl, Tomáš Vyskočil, Jan Šedivý
RNN-CNN combo model: 67.2

Next Steps

Artificial tasks to help design new methods:

- New methods that succeed on all bAbI tasks?
- Make more bAbI tasks to check other skills.

Real tasks to make sure those methods are actually useful:

- Sophisticated reasoning on bAbI tasks doesn't always happen as clearly on <u>real</u> data.. <u>Why? Fix</u>!
- Models that work jointly on <u>**all**</u> tasks so far built.

Dream: can learn from very weak supervision:

We would like to learn in an environment just by communicating with other agents / humans, as well as seeing other agents communicating + acting in the environment.

E.g. a baby talking to its parents, and seeing them talk to each other.

Learning From Human Responses

Mary went to the hallway.

John moved to the bathroom.

Mary travelled to the kitchen.

Where is Mary? A:playground

No, that's incorrect.

Where is John? A:bathroom

Yes, that's right!

If you can predict this, you are most of the way to knowing how to answer correctly.

Human Responses Give Lots of Info

Mary went to the hallway.

John moved to the bathroom.

Mary travelled to the kitchen.

Where is Mary? A:playground

No, the answer is kitchen.

Where is John? A:bathroom

Yes, that's right!

Much more signal than just "No" or zero reward.

Forward Prediction

Mary went to the hallway.

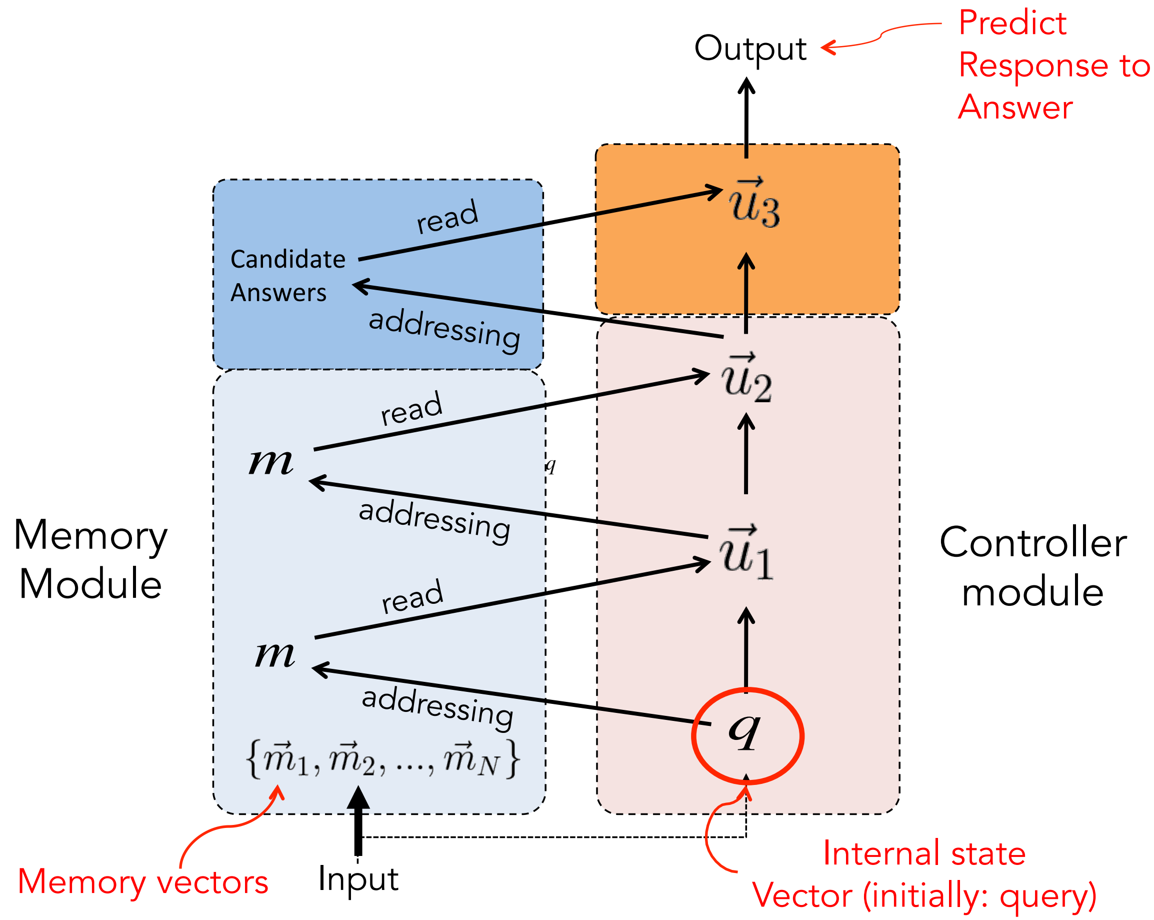
John moved to the bathroom.

Mary travelled to the kitchen.

Where is Mary? A:playground

No, she's in the kitchen.

If you can predict this, you are most of the way to knowing how to answer correctly.



See our new paper! "Dialog-Based Language Learning" arXiv:1604.06045.

FAIR: paper / data / code

- Papers:
  - bAbI tasks: arxiv.org/abs/1502.05698
  - Memory Networks: http://arxiv.org/abs/1410.3916
  - End-to-end Memory Networks: http://arxiv.org/abs/1503.08895
  - Large-scale QA with MemNNs: http://arxiv.org/abs/1506.02075
  - Reading Children's Books: http://arxiv.org/abs/1511.02301
  - Evaluating End-To-End Dialog: http://arxiv.org/abs/1511.06931
  - Dialog-based Language Learning: http://arxiv.org/abs/1604.06045
- Data:
  - bAbI tasks: fb.ai/babi
  - SimpleQuestions dataset (100k questions): fb.ai/babi
  - Children's Book Test dataset: fb.ai/babi
  - Movie Dialog Dataest: fb.ai/babi
- Code:
  - Memory Networks: https://github.com/facebook/MemNN
  - Simulation tasks generator: https://github.com/facebook/bAbI-tasks

RAM Issues

- How to decide what to write and what not to write in the memory?
- How to represent knowledge to be stored in memories?
- Types of memory (arrays, stacks, or stored within weights of model), when they should be used, and how can they be learnt?
- How to do fast retrieval of relevant knowledge from memories when the scale is huge?
- How to build hierarchical memories, e.g. multiscale attention?
- How to build hierarchical reasoning, e.g. composition of functions?
- How to incorporate forgetting/compression of information?
- How to evaluate reasoning models? Are artificial tasks a good way? Where do they break down and real tasks are needed?
- Can we draw inspiration from how animal or human memories work?

Thanks!