# THE NATURAL LANGUAGE DECATHLON: MULTITASK LEARNING AS QUESTION ANSWERING

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MLT Paper Reading Session

# Agenda

- Introduction
- Motivation
- Technical Contribution
- Approach
- Results
- Conclusion

# Introduction

Focus in this paper is multi-task learning. 10 different NLP tasks are jointly learned.

Natural language decathlon (decaNLP) is the benchmark for measuring the performance of the NLP models across ten tasks that appear disparate until unified as question answering.

# Introduction

- Deep learning has improved performance on many NLP tasks individually.

  - **Single-task learning**: Great performance improvement in recent years given {dataset, task, model and metric}

    As long as data is plentiful, we can hill-climb to local optima

# Introduction

- Deep learning has improved performance on many NLP tasks individually.
  - Limits of Single-task learning

1. New task with dataset and metric
2. New Model
3. Train (almost) from scratch
4. Repeat

**human like**

- However, general NLP models cannot emerge within a paradigm that focuses on the particularities of a single metric, dataset, and task.

# What is Next for Natural Language Processing?

- Multi-task learning:

1. Question Answering
2. Machine Translation
3. Summarization
4. Natural language Inference
5. Sentiment analysis
6. Semantic role labeling
7. Relation extraction
8. Goal oriented dialogue
9. Semantic parsing
10. Commonsense pronoun resolution

- Think of which ones might form a basis set of tasks that would help the model understand many different features of language and allow them to design a model that is not particular to any task but can solve all the tasks they want it to work on.

# Motivation

- Why a single Multi-task learning model:

1. Step towards **general AI/NLP** models and Ideas
2. Easy to adopt new tasks
3. Easier deployment in production
4. Lowering the bar for any body to solve their NLP tasks

# Main Contribution

- Introduce the Natural Language Decathlon (decaNLP), a challenge that spans 10 tasks

- Cast all tasks as question answering over a context.

- Present a new multitask question answering network (MQAN) that jointly learns all tasks in decaNLP without any task-specific modules or parameters more effectively than seq2seq and reading comprehension baselines.

# Natural Language Decathlon (decaNLP) Overview

**Examples**

| Question | Context | Answer |
|---|---|---|
| What is a major importance of Southern California in relation to California and the US? | ...Southern California is a major economic center for the state of California and the US.... | major economic center |
| What is the translation from English to German? | Most of the planet is ocean water. | Der Großteil der Erde ist Meerwasser |
| What is the summary? | Harry Potter star Daniel Radcliffe gains access to a reported £320 million fortune... | Harry Potter star Daniel Radcliffe gets £320M fortune... |
| Hypothesis: Product and geography are what make cream skimming work. Entailment, neutral, or contradiction? | Premise: Conceptually cream skimming has two basic dimensions – product and geography. | Entailment |
| Is this sentence positive or negative? | A stirring, funny and finally transporting re-imagining of Beauty and the Beast and 1930s horror film. | positive |

| Question | Context | Answer |
|---|---|---|
| What has something experienced? | Areas of the Baltic that have experienced eutrophication. | eutrophication |
| Who is the illustrator of Cycle of the Werewolf? | Cycle of the Werewolf is a short novel by Stephen King, featuring illustrations by comic book artist Bernie Wrightson. | Bernie Wrightson |
| What is the change in dialogue state? | Are there any Eritrean restaurants in town? | food: Eritrean |
| What is the translation from English to SQL? | The table has column names... Tell me what the notes are for South Australia | SELECT notes from table WHERE 'Current Slogan' = 'South Australia' |
| Who had given help? Susan or Joan? | Joan made sure to thank Susan for all the help she had given. | Susan |

- Dataset with one example from each decaNLP task. Each task is framed as a form of QA. Answer words in red, generated by pointing to the context, in green from the question and in blue if they are generated from the classifier over the full output vocabulary.

# Task definition: Multitask Learning as Question Answering

- Meta-Supervised Learning: From {x, y} to {x, t, y} (t is the task)[1]
- Use a question, q, as a natural description of the task, t, to allow the model to use linguistic information to connect tasks
- y is the answer to q and x is the context necessary to answer q

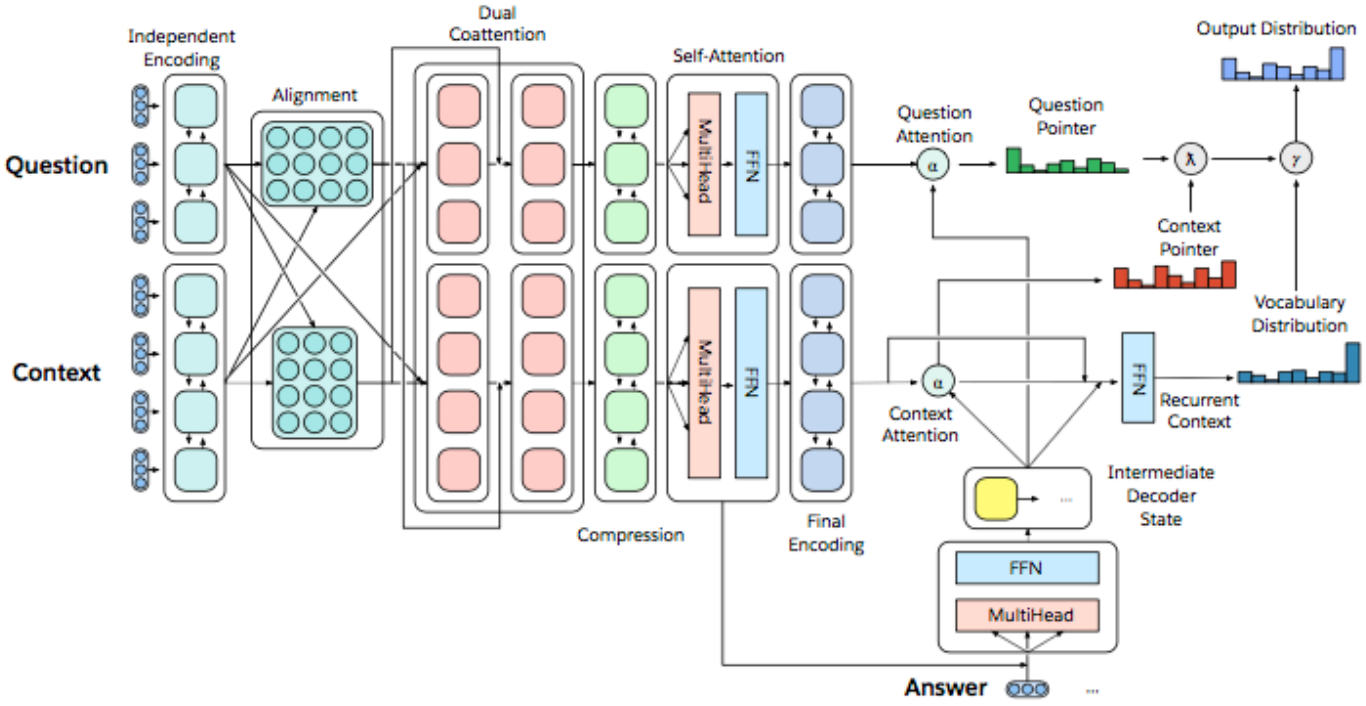
[1][Schmidhuber, 1987, Thrun and Pratt, 1998, Thrun, 1998, Vilalta and Drissi, 2002]

# Task definition: Designing a model for decaNLP

Specifications:

- No task-specific modules or parameters because we assume the task ID is not available
- Must be able to adjust internally to perform desperate tasks
- Should leave open the possibility to zero-shot inference for un seen tasks

# Multi-task Question Answering Network (MQAN) for decaNLP)



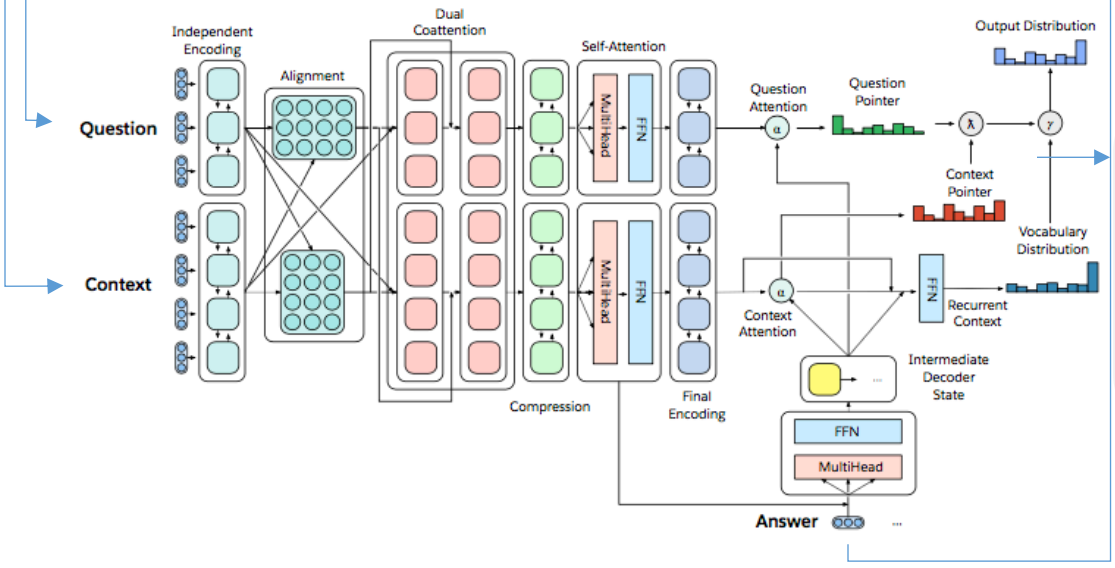

Fixed Glove+Character n-gram embeddings  linear  Shared BiLSTM with skip connection

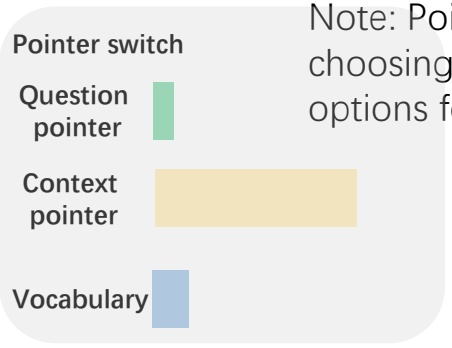
# Multi-task Question Answering Network (MQAN) for decaNLP

**Context**
the **table** has column names··· tell me what the notes are for South Australia

**Question**
what is the translation from English to SQL?

**Answer**
select notes from table where current slogan

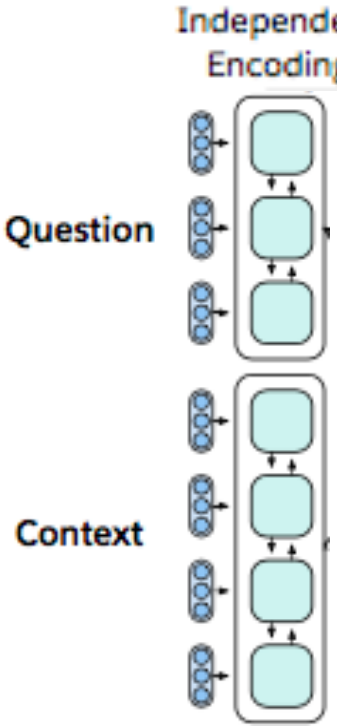



- Start with context
- Ask a question
- Generate answer one word at a time by
  - pointing to context
  - pointing to question
  - Or choosing word from external vocabulary

Note: Pointer switch is choosing from the three options for each output

# Multi-task Question Answering Network (MQAN) for decaNLP)




Input matrices

$$Q \in R^{m \times demb}$$

$$C \in R^{l \times demb}$$

Projected to a common $\boldsymbol{d}$ (linear layer)

$$QW_1 = Q_{proj} \in R^{m \times d}$$

$$CW_1 = C_{proj} \in R^{l \times d}$$

Final BiLSTM layer for both question and context

$$\mathbf{BiLSTM}_{ind}(Q_{proj}) = Q_{ind} \in \mathrm{R}^{m \times d}$$

$$\mathbf{BiLSTM}_{ind}(C_{proj}) = C_{ind} \in \mathrm{R}^{l \times d}$$

Fixed Glove+Character n-gram embeddings → linear → Shared BiLSTM with skip connection

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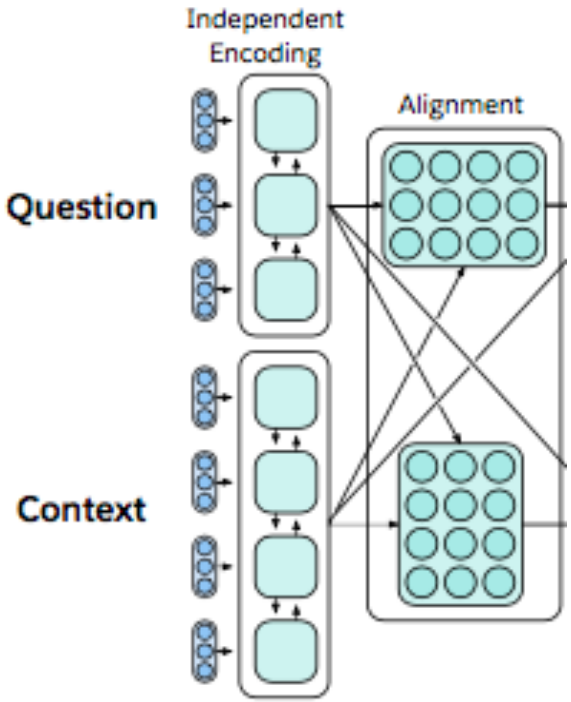



Add trained dummy embeddings

$C_{ind} \in \mathrm{R}^{(l+1)\times d}$

$Q_{ind} \in \mathrm{R}^{(m+1)\times d}$

Avoid forcing tokens
To align with any token
in other sequence

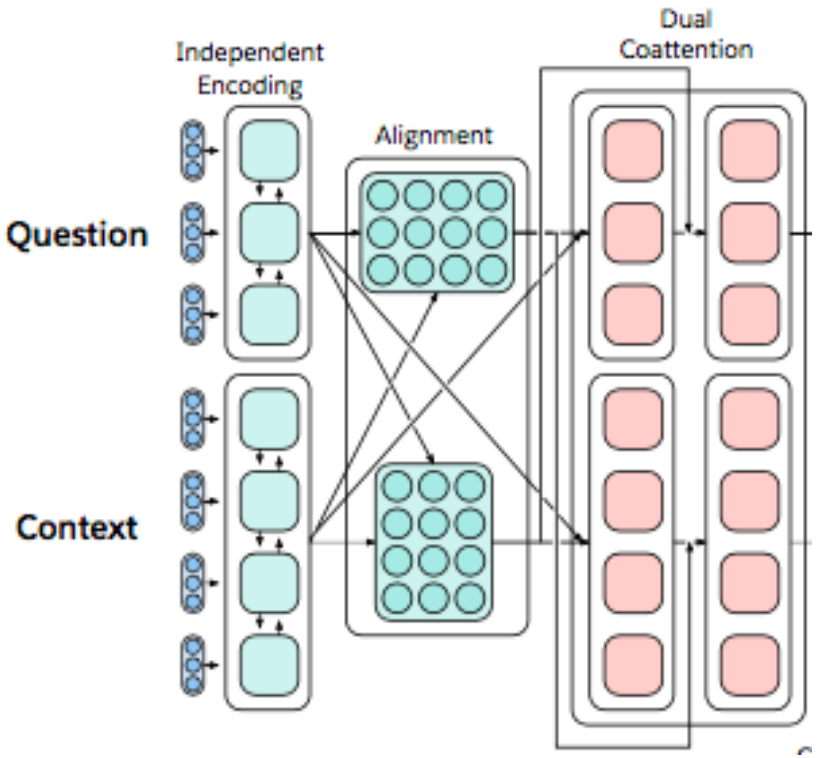
Alignments

$$softmax\,(Q_{ind}C^{\top}_{ind}) = S_{qc} \in R^{(m+1)\times(l+1)}$$

$$softmax\,(C_{ind}Q^{\top}_{ind}) = S_{cq} \in \mathrm{R}^{(l+1)\times(m+1)}$$

We obtain coattended representations by first aligning encoded representations of each sequence

# Multi-task Question Answering Network (MQAN) for decaNLP




Weighted summations

$$S^{\top}_{qc} Q_{ind} = Q_{sum} \in R^{(l+1)\times d}$$

$$S^{\top}_{cq} C_{ind} = C_{sum} \in R^{(m+1)\times d}$$

Transfer alignment info to original sequence

$$S^{\top}_{qc} C_{sum} = C_{coa} \in R^{(l+1)\times d}$$

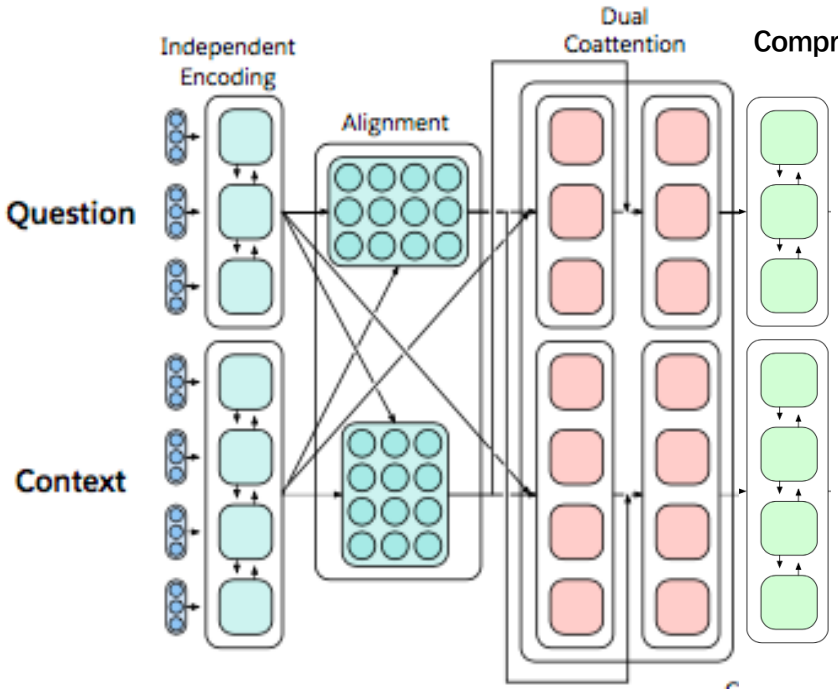
$$S^{\top}_{cq} Q_{sum} = Q_{coa} \in R^{(m+1)xd}$$

Drop dummy embedding

$$Q_{coa} \in R^{mxd} \qquad C_{coa} \in R^{l\times d}$$

Attention summations from one sequence to the other and back again with skip connections

# Multi-task Question Answering Network (MQAN) for decaNLP)



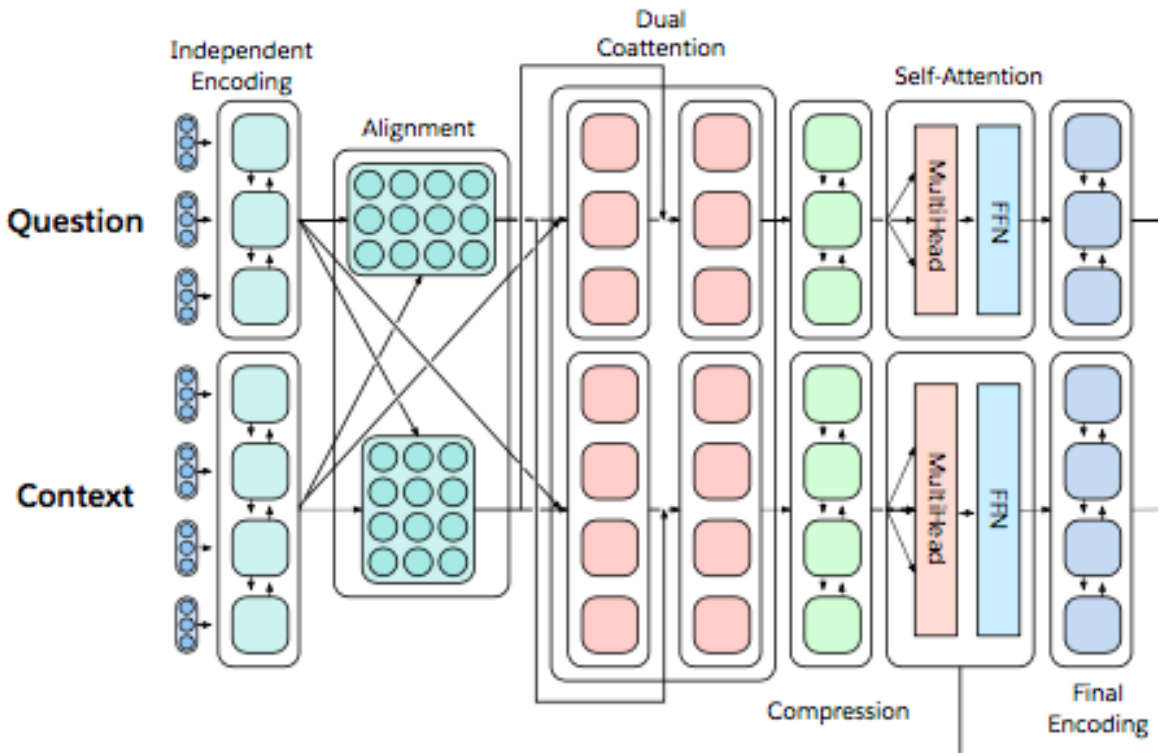

Concatenate all seq representations

$$\mathbf{BiLSTM}_{com}\boldsymbol{Q}\,([\boldsymbol{Q}_{proj}\,;\,\boldsymbol{Q}_{ind};\,\boldsymbol{C}_{sum};\,\boldsymbol{Q}_{coa}]) = \boldsymbol{Q}_{com} \in \boldsymbol{R}^{lxd}$$

$$\mathbf{BiLSTM}_{com}\boldsymbol{C}\,([\boldsymbol{C}_{proj}\,;\,\boldsymbol{C}_{ind};\,\boldsymbol{Q}_{sum};\,\boldsymbol{C}_{coa}]) = \boldsymbol{C}_{com} \in \boldsymbol{R}^{lxd}$$

we concatenate all four prior representations for each sequence along the last dimension and feed into separate BiLSTM

# Multi-task Question Answering Network (MQAN) for decaNLP)



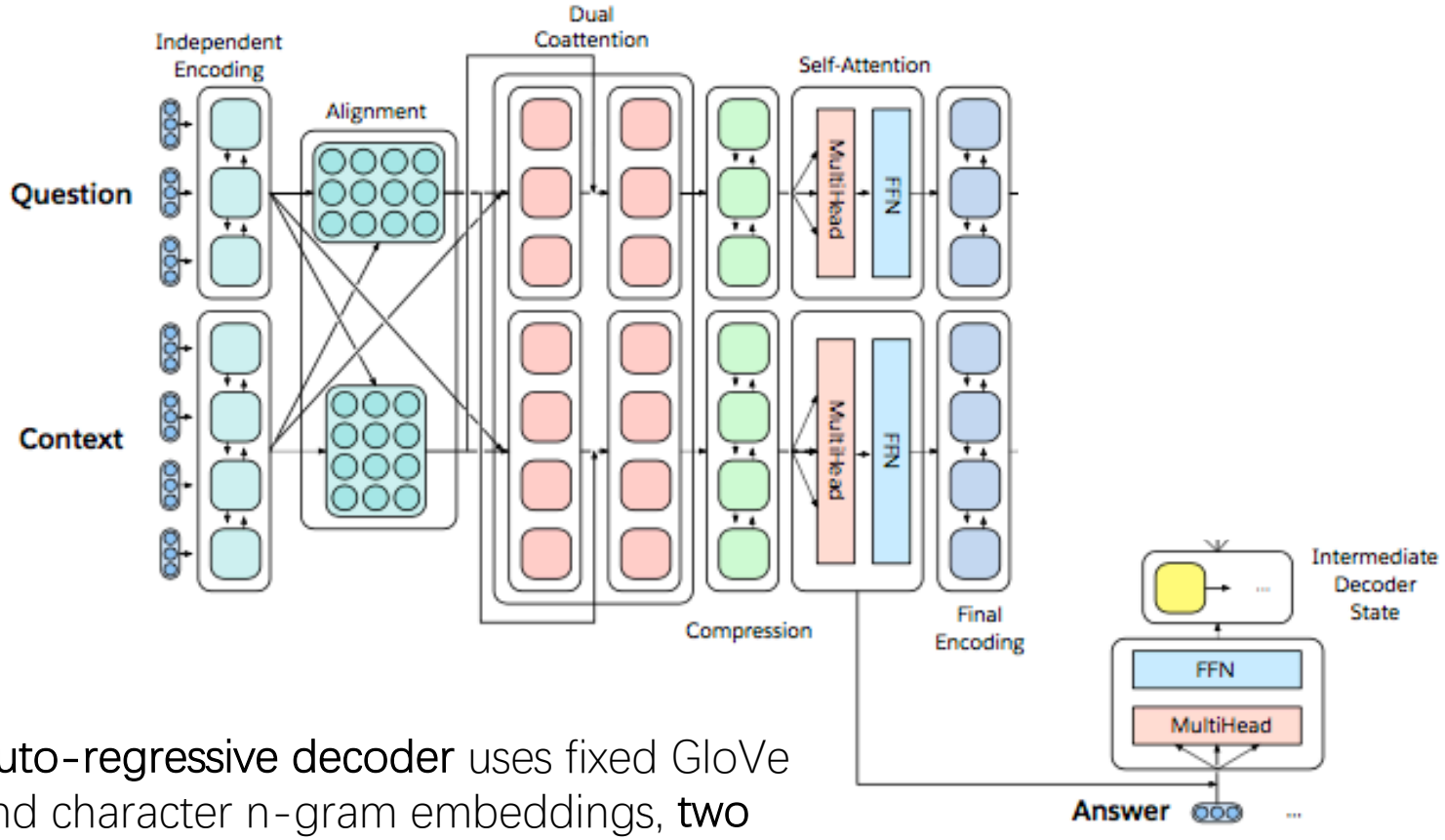

$$\mathbf{BiLSTM}_{finQ}(Q_{self}) = Q_{fin} \in \mathrm{R}^{m \times d}$$

$$\mathbf{BiLSTM}_{finC}(C_{self}) = C_{fin} \in \mathrm{R}^{l \times d}$$

Separate BiLSTMS to reduce dimensionality, two transformer layers, another BiLSTM

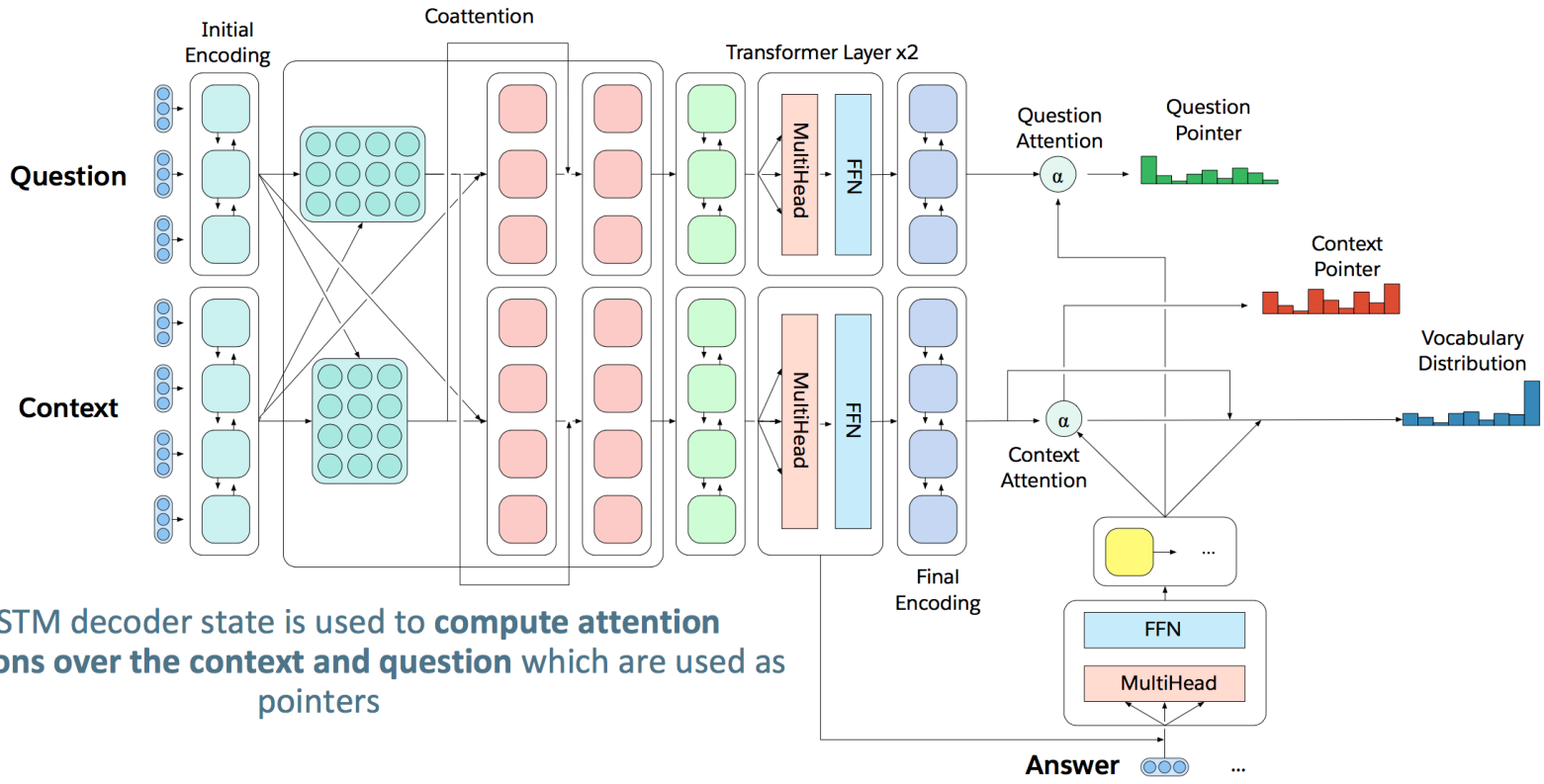
Attention is all you need, NIPS 2017

# Multi-task Question Answering Network (MQAN) for decaNLP



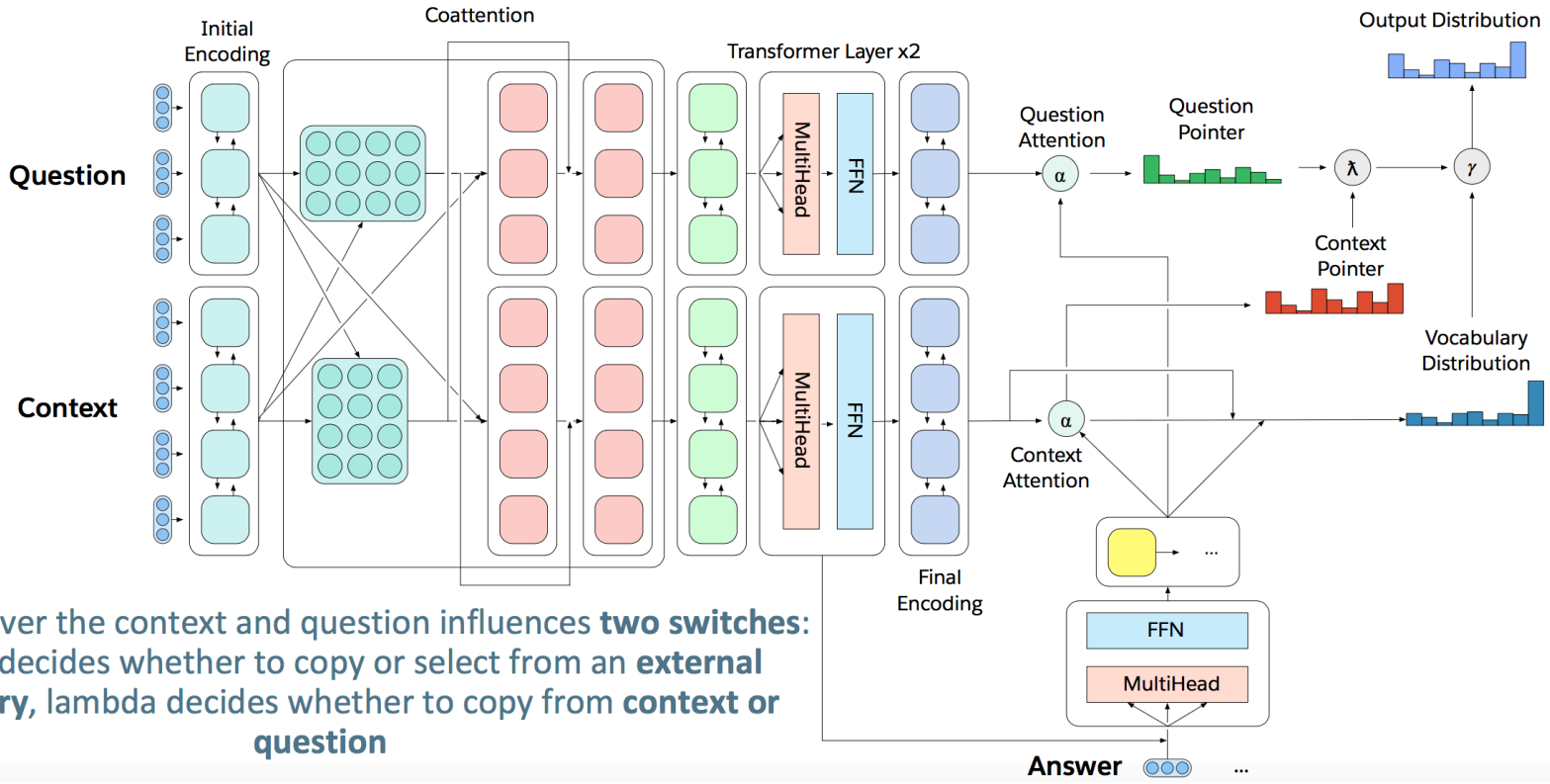

**Auto-regressive decoder** uses fixed GloVe and character n-gram embeddings, **two transformer layers** and an **LSTM layer** that attend to outputs of the last three layers of the encoder

# Multi-task Question Answering Network (MQAN) for decaNLP




The LSTM decoder state is used to **compute attention distributions over the context and question** which are used as pointers

# Multi-task Question Answering Network (MQAN) for decaNLP




Attention over the context and question influences **two switches**: gamma decides whether to copy or select from an **external vocabulary**, lambda decides whether to copy from **context or question**

# Evaluation

Datasets: Different metrics for different tasks

| Task | Dataset | # Train | # Dev | # Test | Metric |
|---|---|---|---|---|---|
| Question Answering | SQuAD | 87599 | 10570 | 9616 | nF1 |
| Machine Translation | IWSLT | 196884 | 993 | 1305 | BLEU |
| Summarization | CNN/DM | 287227 | 13368 | 11490 | ROUGE |
| Natural Language Inference | MNLI | 392702 | 20000 | 20000 | EM |
| Sentiment Analysis | SST | 6920 | 872 | 1821 | EM |
| Semantic Role Labeling | QA-SRL | 6414 | 2183 | 2201 | nF1 |
| Zero-Shot Relation Extraction | QA-ZRE | 840000 | 600 | 12000 | cF1 |
| Goal-Oriented Dialogue | WOZ | 2536 | 830 | 1646 | dsEM |
| Semantic Parsing | WikiSQL | 56355 | 8421 | 15878 | lfEM |
| Pronoun Resolution | MWSC | 80 | 82 | 100 | EM |

nF1: normalized F1 that strips out articles and punctuation
ROUGE: Average of ROUGE-1, 2, and L
EM : exact match comparison (text classification: accuracy)
dsEM: turn-based dialogue state exact match
lfEM: logical forms exact match
cF1: corpus level metric (takes into account that some questions are unanswerable)

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Natural Language Decathlon decascore

decascore = sum of task-specific metrics

# Evaluation

Datasets: Different metrics for different tasks

| | Single-task Training | | | | Multitask Training | | | |
|---|---|---|---|---|---|---|---|---|
| **Dataset** | | | | **(+QPtr)** | | | | **(+QPtr)** |
| SQuAD | | | | 75.3 | | | | 70.8 |
| IWSLT | | | | 26.7 | | | | 16.1 |
| CNN/DM | | | | 25.5 | | | | 23.9 |
| MNLI | | | | 73 | | | | 70.5 |
| SST | | | | 88.5 | | | | 86.2 |
| QA-SRL | | | | 77.9 | | | | 75.8 |
| QA-ZRE | | | | 24.3 | | | | 28 |
| WOZ | | | | 88 | | | | 80.6 |
| WikiSQL | | | | 73.5 | | | | 62 |
| MWSC | | | | 48.8 | | | | 48.8 |
| decaScore | 518.8 | 559.2 | 537.2 | 601.5 | **513.6** | **546.4** | **533.8** | **562.7** |

S2S: is the sequence to sequence baseline
(+Satt): S2S + self Attention in encoder
(+Catt): S2S + self Attention and coattention in the encoder

# Evaluation

Datasets: Different metrics for different tasks

| | Single-task Training | | | | Multitask Training | | | |
|---|---|---|---|---|---|---|---|---|
| **Dataset** | **S2S** | **(+Satt)** | **(+Catt)** | **(+QPtr)** | **S2S** | **(+Satt)** | **(+Catt)** | **(+QPtr)** |
| SQuAD | 48.2 | 68.2 | 74.6 | 75.3 | 47.5 | 66.8 | 71.8 | 70.8 |
| IWSLT | 25 | 23.3 | 26 | 26.7 | 14.2 | 13.6 | 9 | 16.1 |
| CNN/DM | 19 | 20 | 25.1 | 25.5 | 25.7 | 14 | 15.7 | 23.9 |
| MNLI | 67.5 | 68.5 | 34.7 | 73 | 60.9 | 69 | 70.4 | 70.5 |
| SST | 86.4 | 86.8 | 86.2 | 88.5 | 85.9 | 84.7 | 86.5 | 86.2 |
| QA-SRL | 63.5 | 67.8 | 74.8 | 77.9 | 68.7 | 75.1 | 76.1 | 75.8 |
| QA-ZRE | 20 | 19.9 | 16.6 | 24.3 | 28.5 | 31.7 | 28.5 | 28 |
| WOZ | 85.3 | 86 | 86.5 | 88 | 84 | 82.8 | 75.1 | 80.6 |
| WikiSQL | 60 | 72.4 | 72.3 | 73.5 | 45.8 | 64.8 | 62.9 | 62 |
| MWSC | 43.9 | 46.3 | 40.4 | 48.8 | 52.4 | 43.9 | 37.8 | 48.8 |
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Transformer layers, yield benefits in single-task and multitask setting

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Transformer layers, yield benefits in single-task and multitask setting
Question answering and semantic role labeling have a strong connection.

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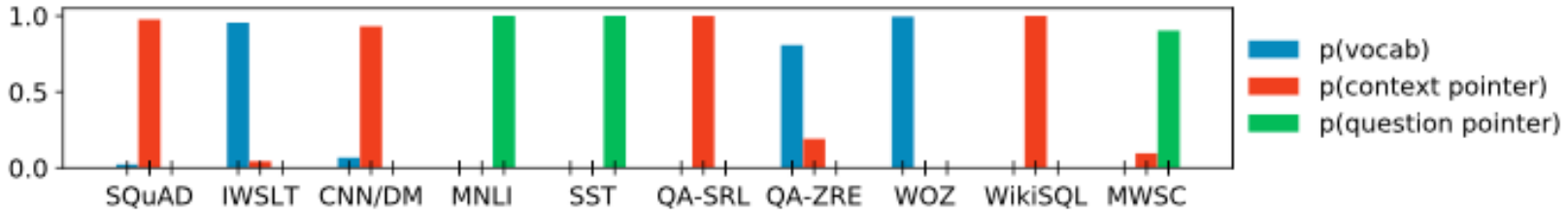
Transformer layers, yield benefits in single-task and multitask setting
Question answering and semantic role labeling have a strong connection.
There is a gap between the combined single task models and the ingle multitask model

# Evaluation




- Answers are correctly copied from either context or question

- No confusion over which tasks the model should perform or which output space to use

# Evaluation

Pretraining on decaNLP improves final performance

- An example: Additional IWSLT Language pairs (Left)
- New tasks like NER (Right)

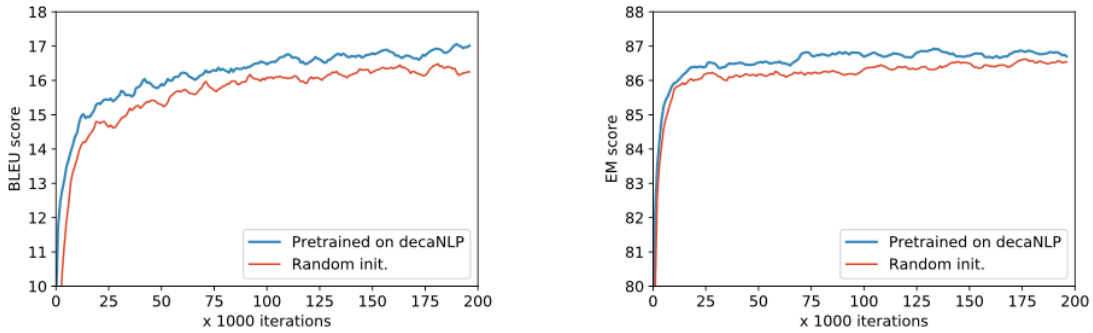



Figure 4: MQAN pretrained on decaNLP outperforms random initialization when adapting to new domains and learning new tasks. Left: training on a new language pair – English to Czech, right: training on a new task – Named Entity Recognition (NER).

# Conclusion

- We introduce (decaNLP) a new benchmark for measuring the performance of NLP models across 10 tasks that appear disparate until unified as QA.
- We present MQAN a model for general question answering that uses muti-pointer-generator decoder to capitalize on questions as natural language descriptions of tasks
- MQAN exhibits transfer-learning and zero-short capabilities.