



# Bidirectional Attention Flow Using Answer Pointer and QANet

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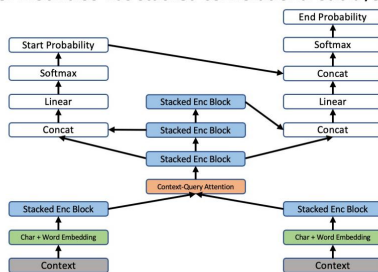
## Introduction

- Machine comprehension is very important for natural language processing (NLP) research [1]
- We propose to replace the regular output layers in the baseline BiDAF with an Answer Pointer [2]
- We also explore and implement QANet [3]
  - Explore both light and complex models
  - Explore both with and without Answer Pointer

**Question:** Why was Tesla returned to Gospie?  
**Context paragraph:** On 24 March 1879, Tesla was returned to Gospie under police guard for not having a residence permit. On 17 April 1879, Mihutin Tesla died at the age of 60 after contracting an unspecified illness (although some sources say that he died of a stroke). During that year, Tesla taught a large class of students in his old school, Higher Real Gymnasium, in Gospie.  
**Answer:** not having a residence permit

## QANet

QANet is very similar to Transformer but its main component Encoder Block also has stacked convolutional sublayers.



## Discussion

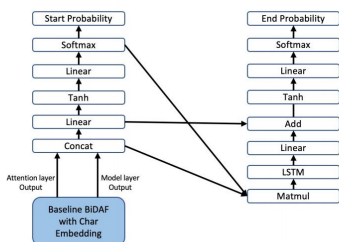
Model	Dev F1	Dev EM
BIDAF Baseline	58.26	55.05
BIDAF Baseline + Char Embedding	61.52	58.21
BIDAF Baseline + Char Embedding + Answer Pointer	62.18	59.13
QANet v1 + Char Embedding	61.69	58.01
QANet v1 + Char Embedding + Answer Pointer	64.35	60.93
QANet v2 + Char Embedding + Answer Pointer	68.29	64.98

Challenges / Limitations

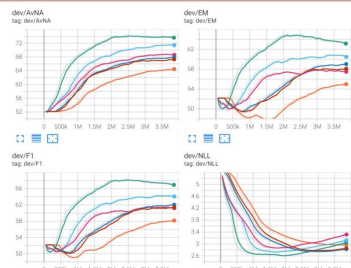
- Longer answer performs worse than shorter answer
- "Why" question type performs worse than other question types

## Answer Pointer

The Answer Pointer conditions the probability distribution for the end location on the start location



## Experiment



- BIDAF Baseline
- BIDAF Baseline + Char Embedding
- BIDAF Baseline + Char Embedding + Answer Pointer
- QANet v1 + Char Embedding
- QANet v1 + Char Embedding + Answer Pointer
- QANet v2 + Char Embedding + Answer Pointer

## Summary

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- Integrating Answer Pointer to BiDAF and QANet improves F1 and EM performance.
- Larger QANet performance better than lighter QANet.

Future Work

- Explore Transformer-XL for longer-term dependencies.
- Explore models with low memory use like Reformer.

**Reference**  
 [1] Seo, Minjoon, et al. "Bidirectional attention flow for machine comprehension." arXiv preprint arXiv:1611.01603  
 [2] Shuohang Wang and Jing Jiang. Machine comprehension using match-lstm and answer pointer. International Conference on Learning Representations (ICLR), 2017.  
 [3] Adams Wei Yu, David Dohan, Minh-Thang Luong, Rui Zhao, Kai Chen, Mohammad Norouzi, and Quoc V Le. QANet: Combining local convolution with global self-attention for reading comprehension. arXiv preprint arXiv:1804.09541, 2018.