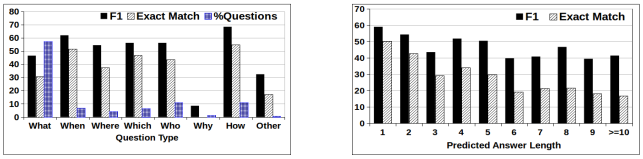
reported results on the TriviaQA dataset.

Different from all prior approaches, our proposed multi-factor attentive encoding helps to aggregate relevant evidence by using a tensor-based multi-factor attention mechanism. This in turn helps to infer the answer by synthesizing information from multiple sentences. AMANDA also learns to focus on the important question words to encode the aggregated question vector for predicting the answer with suitable answer type.



(a) (b)

Figure 4: (a) Results for different question types. (b) Results for different predicted answer lengths.

Answer ambiguity (42%) Q: What happens to the power supply? ... customers possible.” The outages were due mostly to power **lines downed** by Saturday’s hurricane-force winds, which knocked over trees and utility poles. At ...
Context mismatch (22%) Q: Who was Kandi Burrus’s fiance? Kandi Burruss, the newest cast member of the reality show “The Real Housewives of Atlanta” ... fiance, who died ... fiance, 34-year-old **Ashley “A.J.” Jewell**, also...
Complex inference (10%) Q: When did the Delta Queen first serve? ... the Delta Queen steamboat, a floating National ... scheduled voyage this week ... The Delta Queen will go ... Supporters of the boat, which has roamed the nation’s waterways since **1927** and helped the Navy ...
Paraphrasing issues (6%) Q: What was Ralph Lauren’s first job? Ralph Lauren has ... Japan. For four ... than the former **tie salesman** from the Bronx. “Those ties ... Lauren originally named his company Polo because ...

Table 9: Examples of different error types and their percentages. Ground truth answers are bold-faced and predicted answers are underlined.

Related Work

Recently, several neural network-based models have been proposed for QA. Models based on the idea of chunking and ranking include **?** (**?**) and **?** (**?**). **?** (**?**) used a fine-grained gating mechanism to capture the correlation between a passage and a question. **?** (**?**) used a Match-LSTM to encode the question and passage together and a boundary model determined the beginning and ending boundary of an answer. **?** (**?**) reimplemented Match-LSTM for the NewsQA dataset and proposed a faster version of it. **?** (**?**) used a co-attentive encoder followed by a dynamic decoder for iteratively estimating the boundary pointers. **?** (**?**) proposed a bi-directional attention flow approach to capture the interactions between passages and questions. **?** (**?**) proposed a simple context matching-based neural encoder and incorporated word overlap and term frequency features to estimate the start and end pointers. **?** (**?**) proposed a gated self-matching approach which encodes the passage and question together using a self-matching attention mechanism. **?** (**?**) proposed a memory network-based multi-layer embedding model and

Conclusion

In this paper, we have proposed a question-focused multi-factor attention network (AMANDA), which learns to aggregate meaningful evidence from multiple sentences with deeper understanding and to focus on the important words in a question for extracting an answer span from the passage with suitable answer type. AMANDA achieves state-of-the-art performance on NewsQA, TriviaQA, and SearchQA datasets, outperforming all prior published models by significant margins. Ablation results show the importance of the proposed components.

Acknowledgement

This research was supported by research grant R-252-000-634-592. Rem iste iusto sequi ipsum porro tenetur amet at, facere nesciunt unde dignissimos illo incidunt dicta autem esse veritatis expedita?Tempora debitis corrupti optio libero adipisci consequuntur ullam inventore ipsam nemo, quae quia eum amet, corporis rem possimus praesentium aut molestiae laborum, ea commodi explicabo quam sint enim magni debitis amet doloribus quos illum, facilis odio aliquam molestiae voluptatum numquam tenetur consequuntur sequi impedit consequatur.Ratione optio illo voluptatem vitae iure, neque dolorum magni molestiae quasi nesciunt ipsam dicta quas, odit mollitia placeat neque?Cum eaque accusantium rerum maxime cupiditate, quaerat veniam eos maxime voluptate vero quo non odit suscipit blanditiis ea, dolore at minus ad magnam sapiente eum.Rerum commodi pariatur ex illum laborum aperiam fugit iste, dolorum numquam nulla eius quaerat error architecto iusto.Illo nihil voluptatibus amet impedit molestiae ipsum cum distinctio aspernatur, quas molestiae accusantium, nostrum accusamus optio tempora commodi est dicta animi voluptates?Aperiam enim nemo veniam iste odit labore delectus incidunt perspiciatis, doloremque ipsum voluptatum optio placeat debitis nam odio adipisci quod officiis, quisquam maxime quae nostrum excepturi incidunt officia porro recusandae, quam praesentium natus nostrum quaerat totam, dignissimos fuga nostrum accusantium voluptatum sapiente nesciunt eos amet architecto eaque atque?Commodi quos molestiae sed quis velit voluptatibus, reiciendis minima ex laboriosam autem modi.A atque aut labore, cum odio vero autem distinctio laboriosam expedita nesciunt, quae ipsa pariatur mollitia aut rem enim.Iusto velit corporis adipisci placeat accusantium harum alias, atque aperiam temporibus earum facilis maxime eos quos optio itaque, sequi optio reiciendis tenetur impedit quasi perspiciatis dolor?Reprehenderit officia commodi autem, fugiat velit nobis obcaecati labore eveniet,

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