One Framework to Run them All: A Unified Framework for Reading Comprehension Style Question Answering Systems

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List of Papers :

- B. Dhingra, H. Liu, Z. Yang, W. W. Cohen, and R. Salakhutdinov. **Gated-attention readers for text comprehension**. In Proceedings of the55th Annual Meeting of the Association for Computational Linguistics,ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 1832–1846, 2017. doi: 10.18653/v1/P17-1168.
- M. J. Seo, A. Kembhavi, A. Farhadi, and H. Hajishirzi. **Bidirectional attention flow for machine comprehension**.CoRR, abs/1611.01603, 2016.
- C. Xiong, V. Zhong, and R. Socher. **Dynamic coattention networks forquestion answering**. CoRR, abs/1611.01604, 2016.
- W. Wang, N. Yang, F. Wei, B. Chang, and M. Zhou. **Gated self-matching networks for reading comprehension and question answering**. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1:Long Papers, pages 189–198, 2017.
- K. M. Hermann, T. Kocisk ́y, E. Grefenstette, L. Espeholt, W. Kay,M. Suleyman,and P. Blunsom. **Teaching machines to read and comprehend**. In Advances in Neural Information Processing Systems 28:Annual Conference on Neural Information Processing Systems 2015,December 7-12,2015,Montreal,Quebec,Canada, pages 1693–1701, 2015.

Reading Comprehension Style QA

PASSAGE

The role of teacher is often formal and ongoing, carried out at a school or other place of formal education. In many countries, a person who wishes to become a teacher must first obtain specified professional qualifications or credentials from a university or college. These professional qualifications may include the study of pedagogy, the science of teaching. Teachers, like other professionals, may have to continue their education after they qualify, a process known as continuing professional development. Teachers may use a **lesson plan** to facilitate student learning, providing a course of study which is called **the curriculum.**

Query: ***What is a course of study called?***

Answer: ***The curriculum***

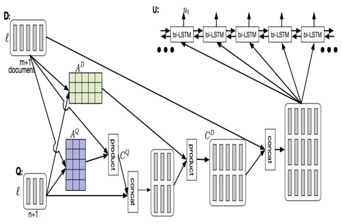
Query: **What can a teacher use to help students learn?**

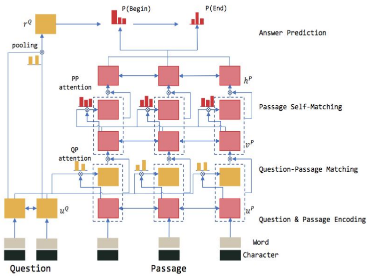
Answer: ***lesson plan***

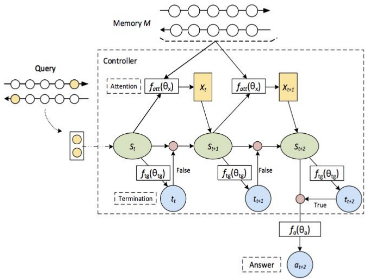
Current Datasets

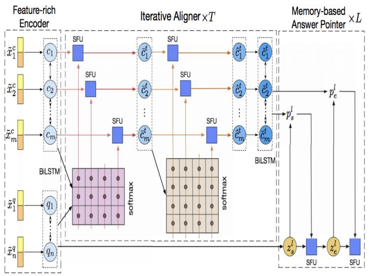
Datasets	Question Source	Formulation	Size
CNN/Dailymail[9]	summary + Cloze	fill in single entity	1.4M
CBT[10]	Cloze	fill in single entity	688K
SQuAD[26]	crowdsourced	spans in passages	100K
RACE[17]	Standardized tests	Multiple choice	80K
MS-Marco[23]	query logs	Human generated	+100K
Trivia-QA[14]	query logs	answer span	95K
MCTest[27]	crowdsourced	multiple choice	2640
WDW[24]	Cloze	fill in single entity	+185K

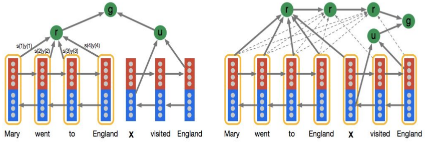
Wave of Neural RCQA models:





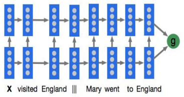




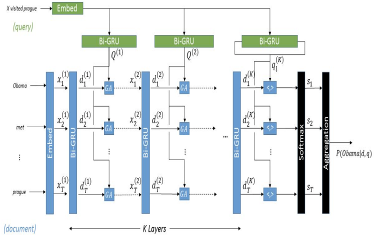


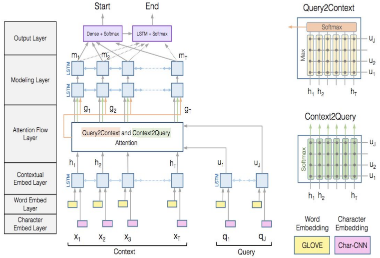
(a) Attentive Reader.

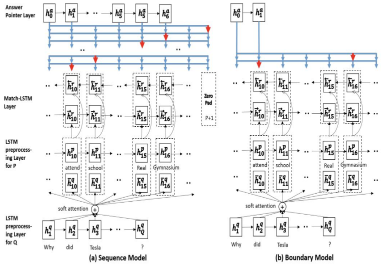
(b) Impatient Reader.



(c) A two layer Deep LSTM Reader with the question encoded before the document.





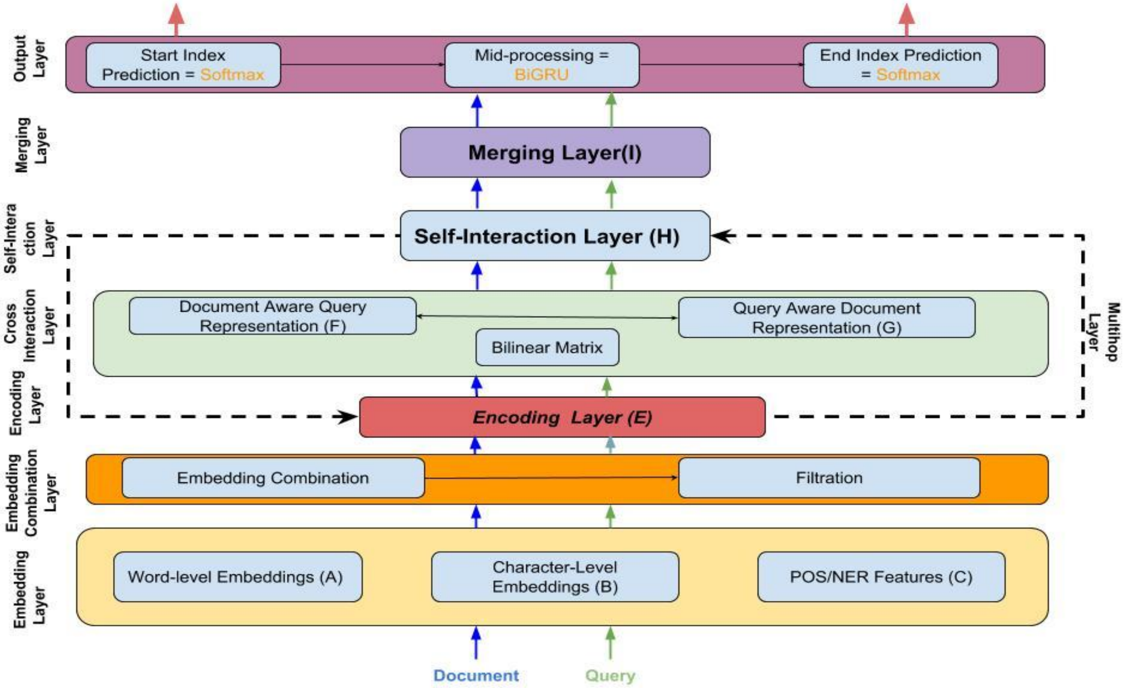


The Problem:

- Too many models..
- Each work fine-tunes a different module to beat the state-of-the-art performance

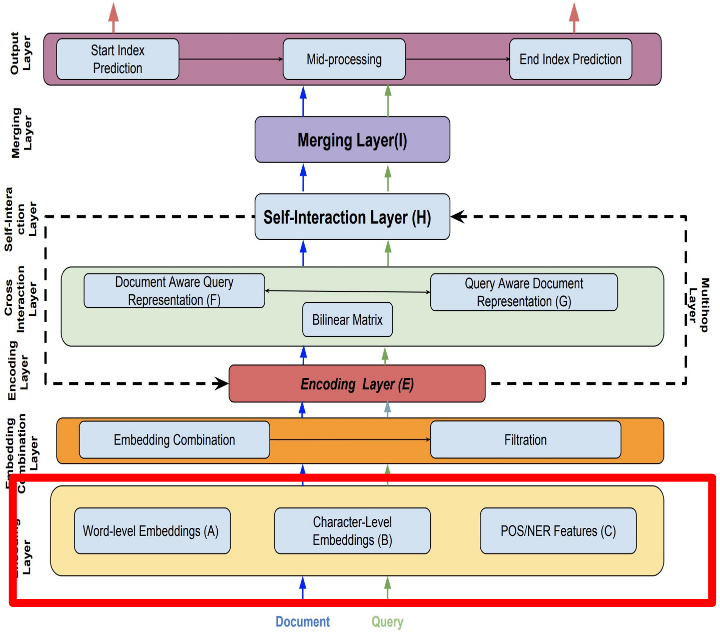
Need a common platform to analyze all the works in an apples-to-apples fashion

Proposed RCQA Framework



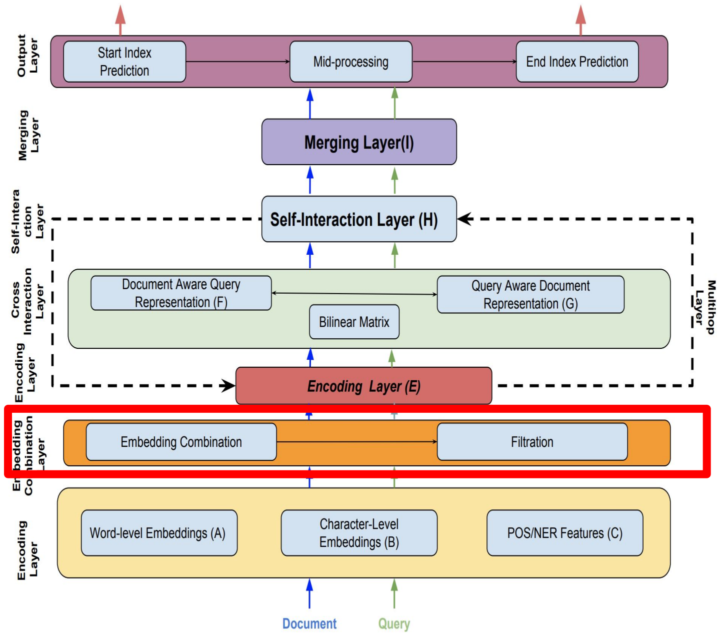
Embedding Layer

- **Objective:** Each word in query and passage could be represented as a *d*-dimensional vector
- **Modules:**
  - Word Embedding Module
  - Character Embedding Module
  - POS/NE/TF-IDF Features Module
- *Existing Works using this layer:*
  - **ALL**



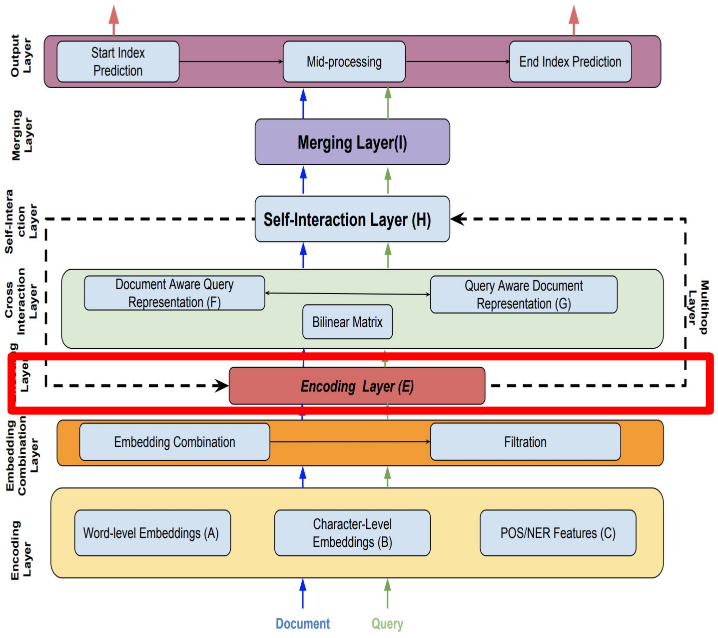
Embedding Aggregation Layer

- **Objective:** If more than one module is used in the previous layer, this layer combines the different vector representations of the same word
- **Methods for Aggregation**
  - Concatenation
  - Algebraic Sum
  - Scalar Gate
  - Vector Gate
- *Existing Works using this layer:*
  - [6], [37], [29], [8], [32]



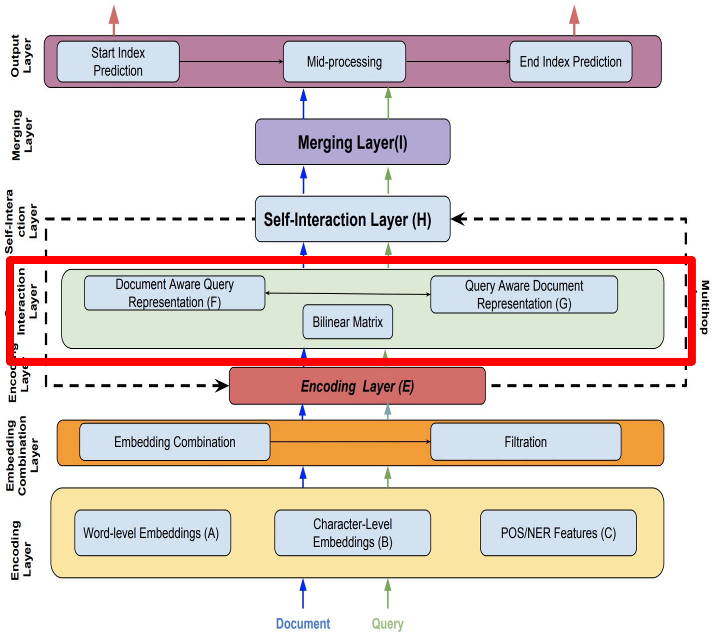
Encoding Layer

- **Objective:** Contextual information for each of the word in the document and query is encoded using RNNs:
- **Methods for Encoding:**
  - Bidirectional LSTMs
  - Stacked Bidirectional LSTMs
  - Deep LSTMs with skip connections across layers
- *Exisiting Works Using this layer*
  - **ALL**



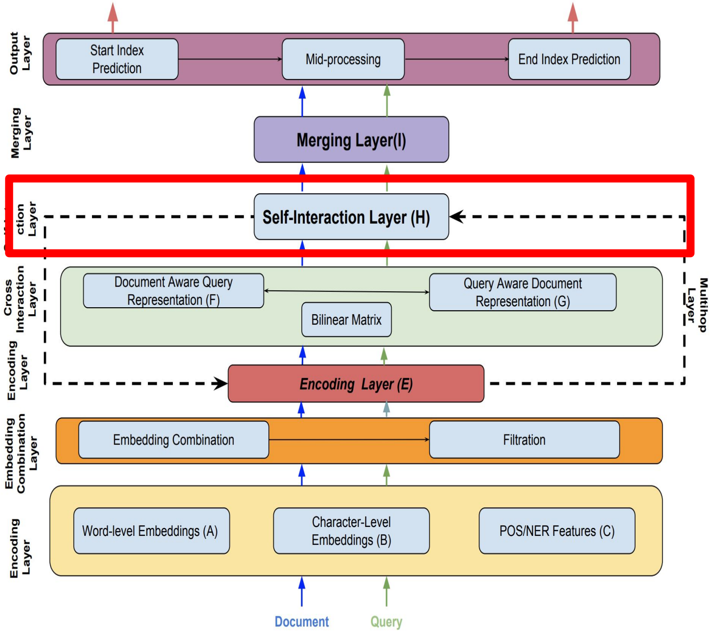
Cross Interaction Layer

- **Objective:** Captures the interaction between document and query, either at word level or sentence-level
- **Modules**:
    - Document Aware Query Representation: Read document in light of the query
    - Query Aware Document Representation: Read query in light of the document
    - Bilinear Matrix: Captures word-word interaction between query and document
- *ExistingWorks Using this layer*
    - **ALL**



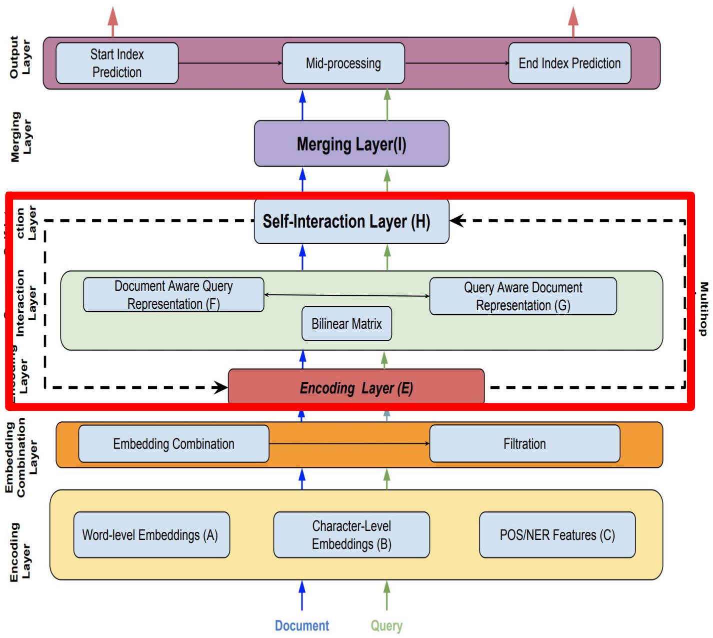
Self Interaction Layer

- **Motivation:** To infer some of the answer, it is necessary to infer from more than one sentence in a document (might not be continuous)
- **Objective**: Capture long term dependency by computing word-word interaction of every document word pair
- **Module**:
  - Bilinear Matrix
- *Existing Works Using this layer*
  - [8],[29],[12],[35]



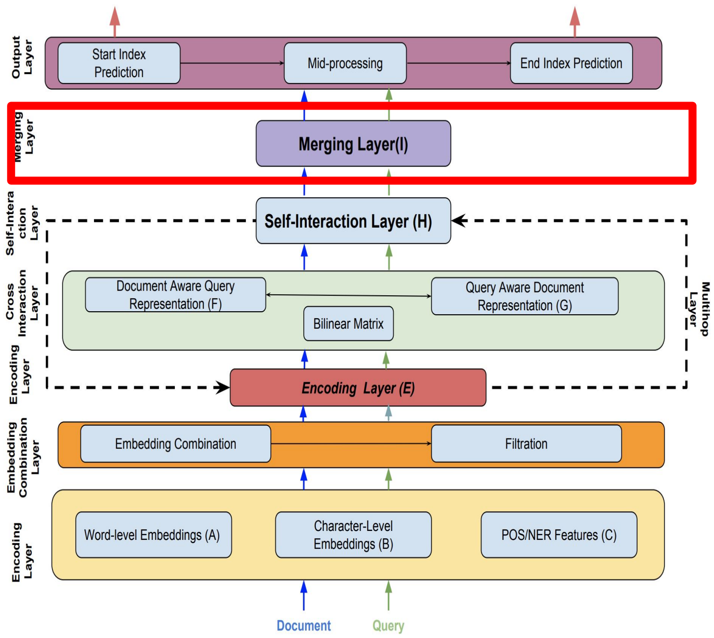
Multihop Layer

- **Motivation:** Documents need to be re-read a couple of times to be confident about the answer
- **Objective**: Decides on how many times document needs to be re-read and ensures information flow is consistent from self-interaction layer to encoding layer
- **Module**:
  - Bilinear Matrix
- *Existing Works Using this layer*
  - [30], [6], [31]



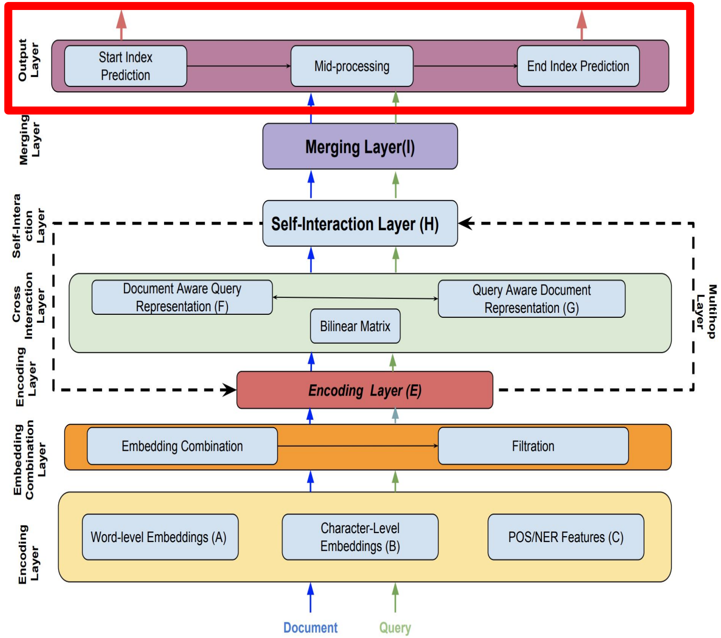
Merging Layer

- **Objective**: Merge the representations obtained using cross-interaction and self-interaction layers
- **Module**:
  - Bilinear Matrix
- *Existing Works Using this layer*
  - **ALL**



Ouput Layer

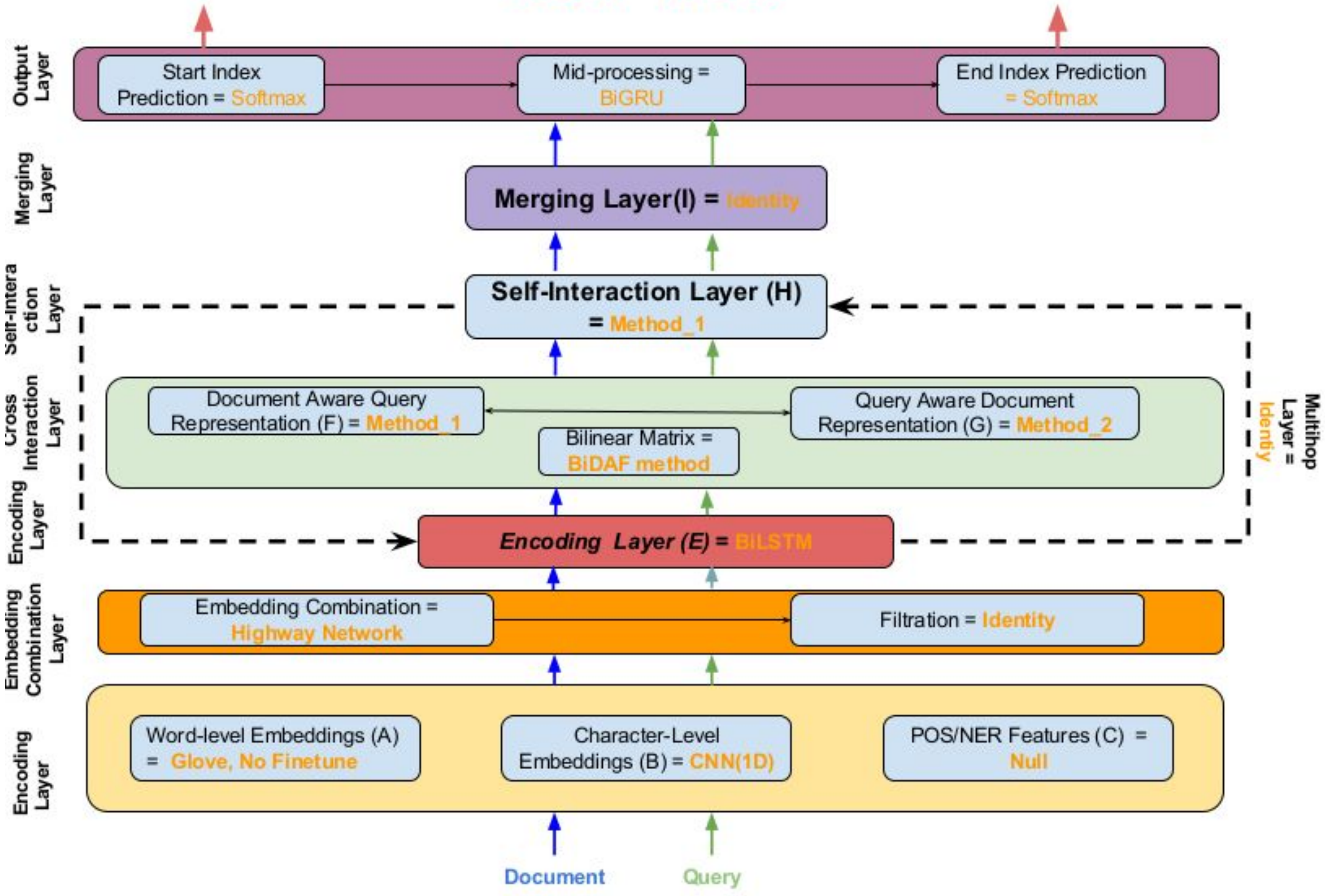
- **Objective**: Uses the representation obtained from merging layer to predict the correct span or generate the answer in natural language
- *Existing Works Using this layer*
  - **ALL**



Conclusion

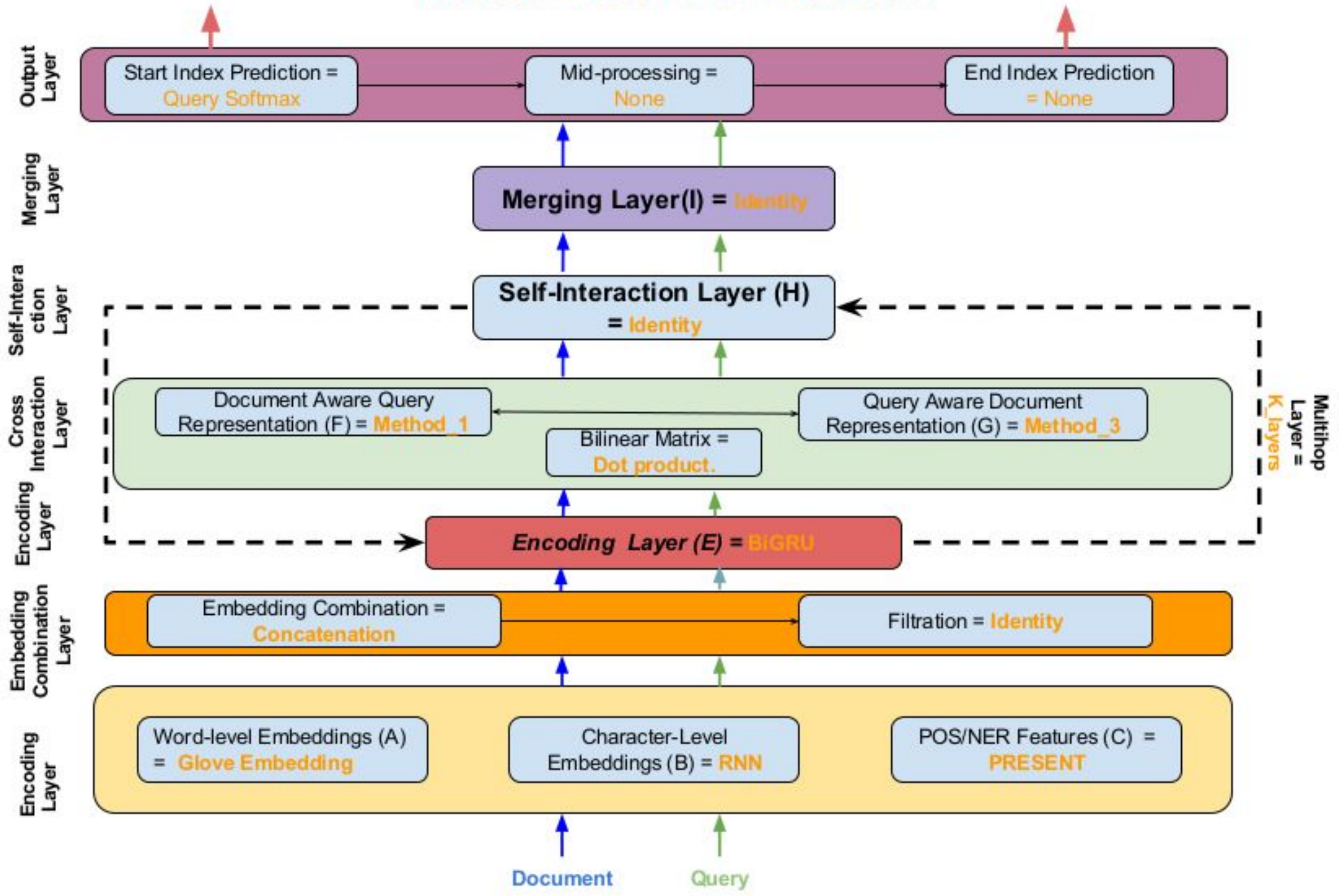
- This unified framework will help us understand, the plethora of concepts introduced in RCQA models, better
- This framework would help in comparing the efficacy of different modules/models

BiDAF Model

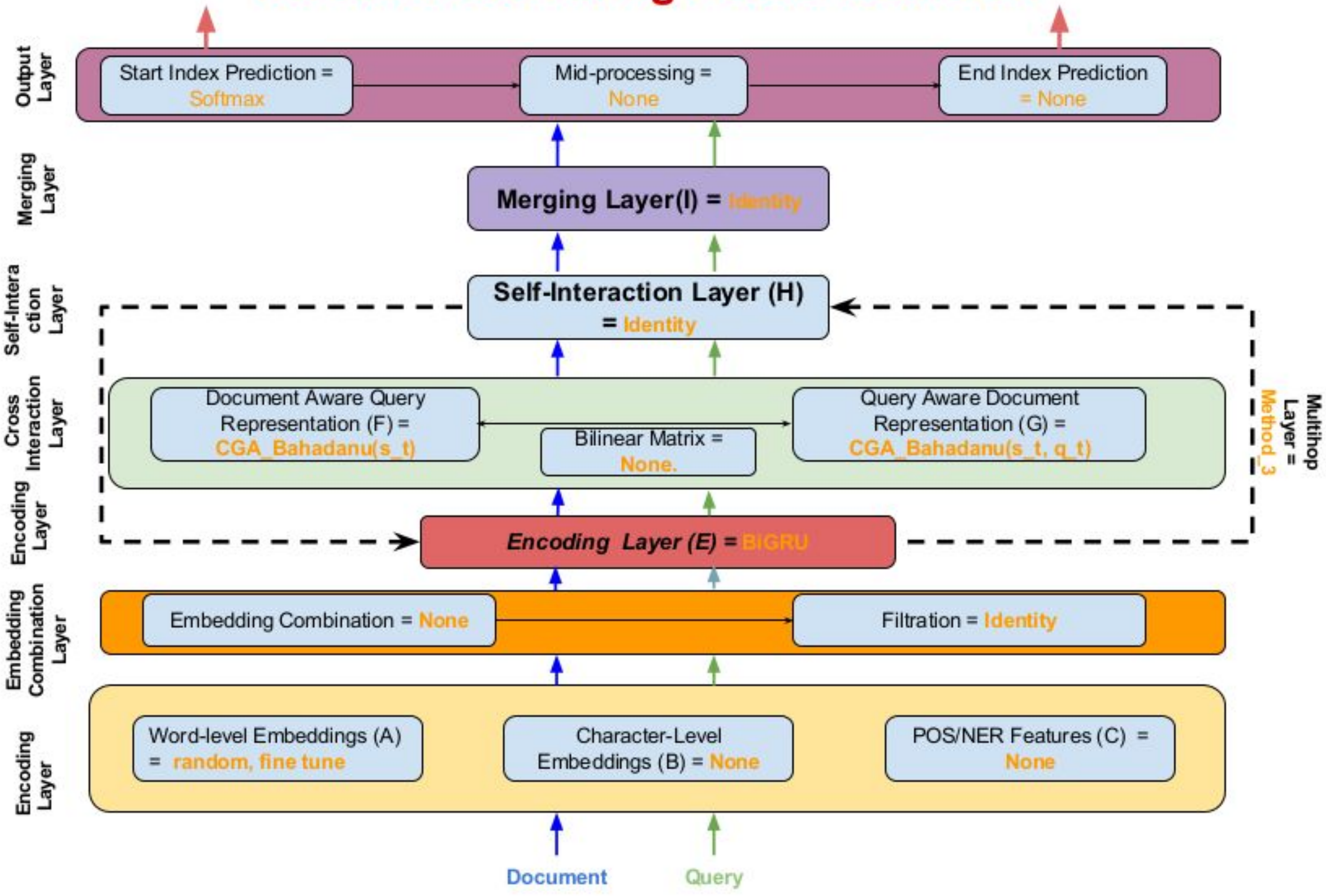


Output Layer
Start Index Prediction = Softmax
Mid-processing = BiGRU
End Index Prediction = Softmax
Merging Layer
Merging Layer(I) = Identity
Self-Interaction Layer
Self-Interaction Layer (H) = Method_1
Cross Interaction Layer
Document Aware Query Representation (F) = Method_1
Query Aware Document Representation (G) = Method_2
Bilinear Matrix = BiDAF method
Multihop Layer = Identiy
Encoding Layer
Encoding Layer (E) = BiLSTM
Embedding Combination Layer
Embedding Combination = Highway Network
Filtration = Identity
Encoding Layer
Word-level Embeddings (A) = Glove, No Finetune
Character-Level Embeddings (B) = CNN(1D)
POS/NER Features (C) = Null
Document
Query

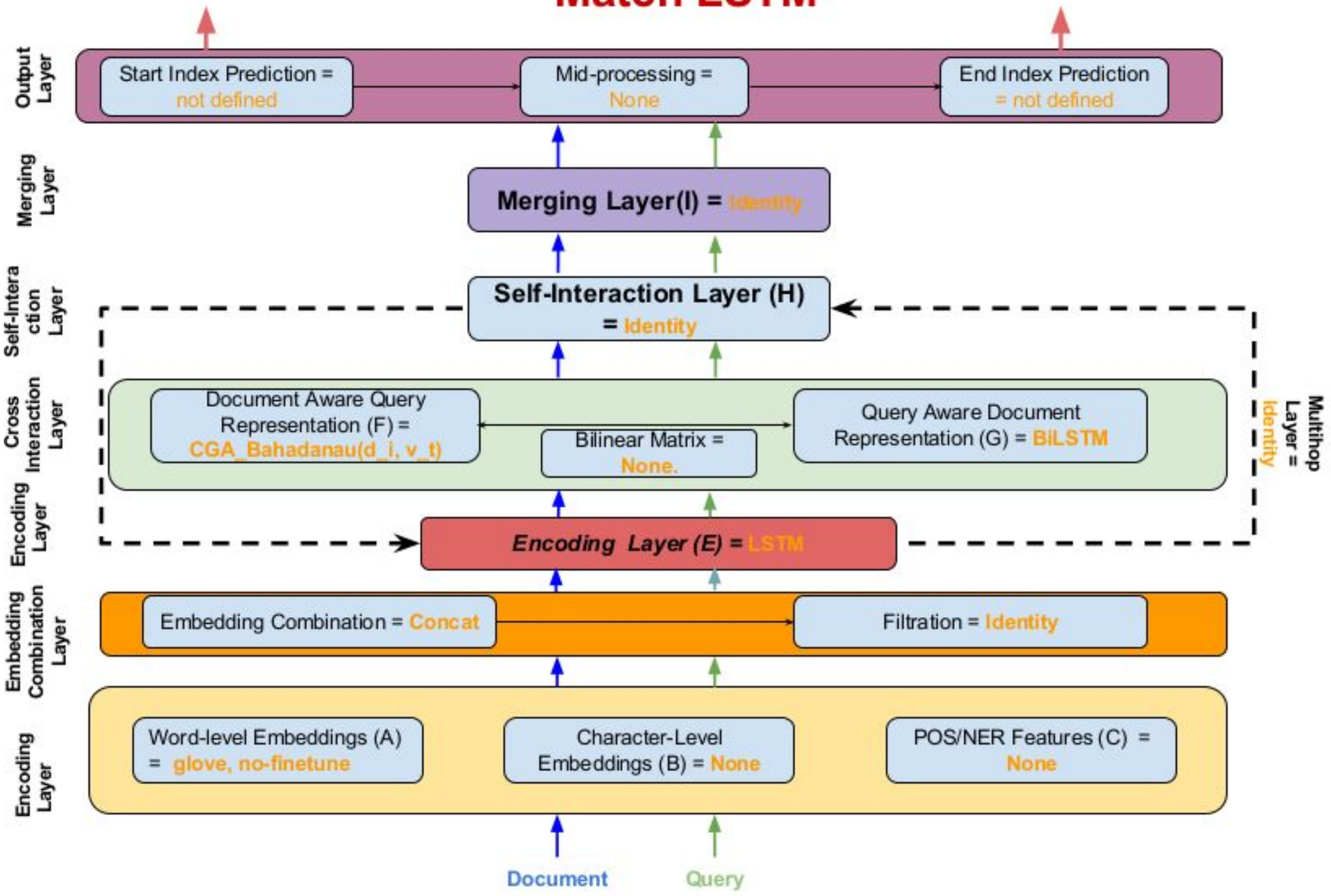
Gated Attention Reader



Iterative Alternating Neural Attention

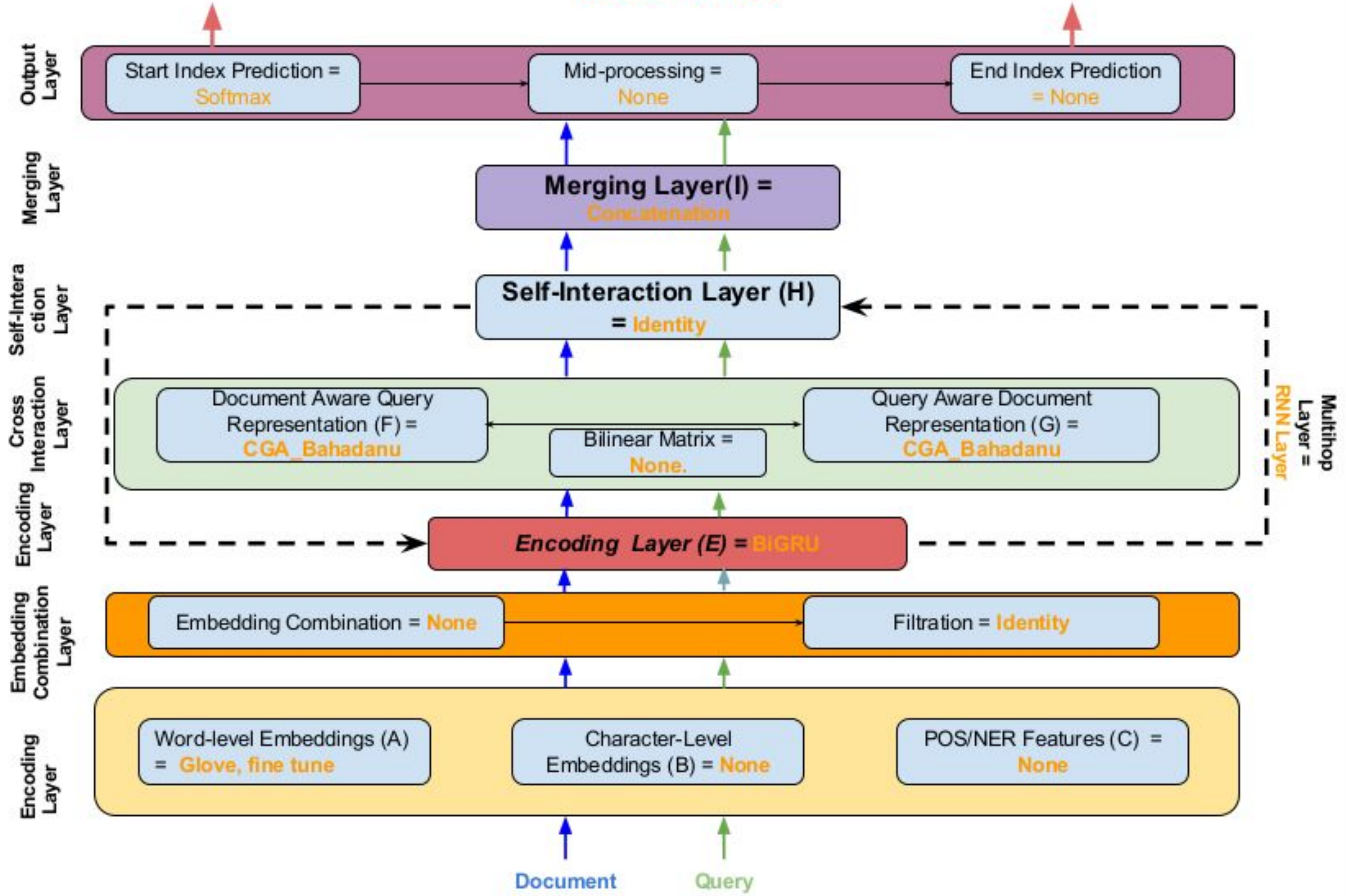


Match LSTM



Output Layer
Start Index Prediction = not defined
Mid-processing = None
End Index Prediction = not defined
Merging Layer
Merging Layer(I) = Identity
Self-Interaction Layer
Self-Interaction Layer (H) = Identity
Cross Interaction Layer
Document Aware Query Representation (F) = CGA_Bahadanau(d_i, v_t)
Bilinear Matrix = None.
Query Aware Document Representation (G) = BiLSTM
Multihop Layer = Identity
Encoding Layer
Encoding Layer (E) = LSTM
Embedding Combination Layer
Embedding Combination = Concat
Filtration = Identity
Encoding Layer
Word-level Embeddings (A) = glove, no-finetune
Character-Level Embeddings (B) = None
POS/NER Features (C) = None
Document
Query

Reasonet



Output Layer
Start Index Prediction = Softmax
Mid-processing = None
End Index Prediction = None
Merging Layer
Merging Layer(I) = Concatenation
Self-Interaction Layer
Self-Interaction Layer (H) = Identity
Cross Interaction Layer
Document Aware Query Representation (F) = CGA_Bahadanu
Bilinear Matrix = None.
Query Aware Document Representation (G) = CGA_Bahadanu
Multihop Layer = RNN Layer
Encoding Layer
Encoding Layer (E) = BiGRU
Embedding Combination Layer
Embedding Combination = None
Filtration = Identity
Encoding Layer
Word-level Embeddings (A) = Glove, fine tune
Character-Level Embeddings (B) = None
POS/NER Features (C) = None
Document
Query

Questions ?

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