Multi-dimensional feature merger for Question Answering

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Columbia University
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Joint work with: William Murdock, Jennifer Chu-carroll, Adam Lally, Aditya Kalyanpur (IBM Research)

Question Answering

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(Question) This large land animal also has large ears.

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(Candidate Answer) African Elephant

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(Supporting passages)

Question Answering

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(Supporting passages)
1) African Elephant is a large land animal

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-- Watson tries to find the best passage that supports the answer

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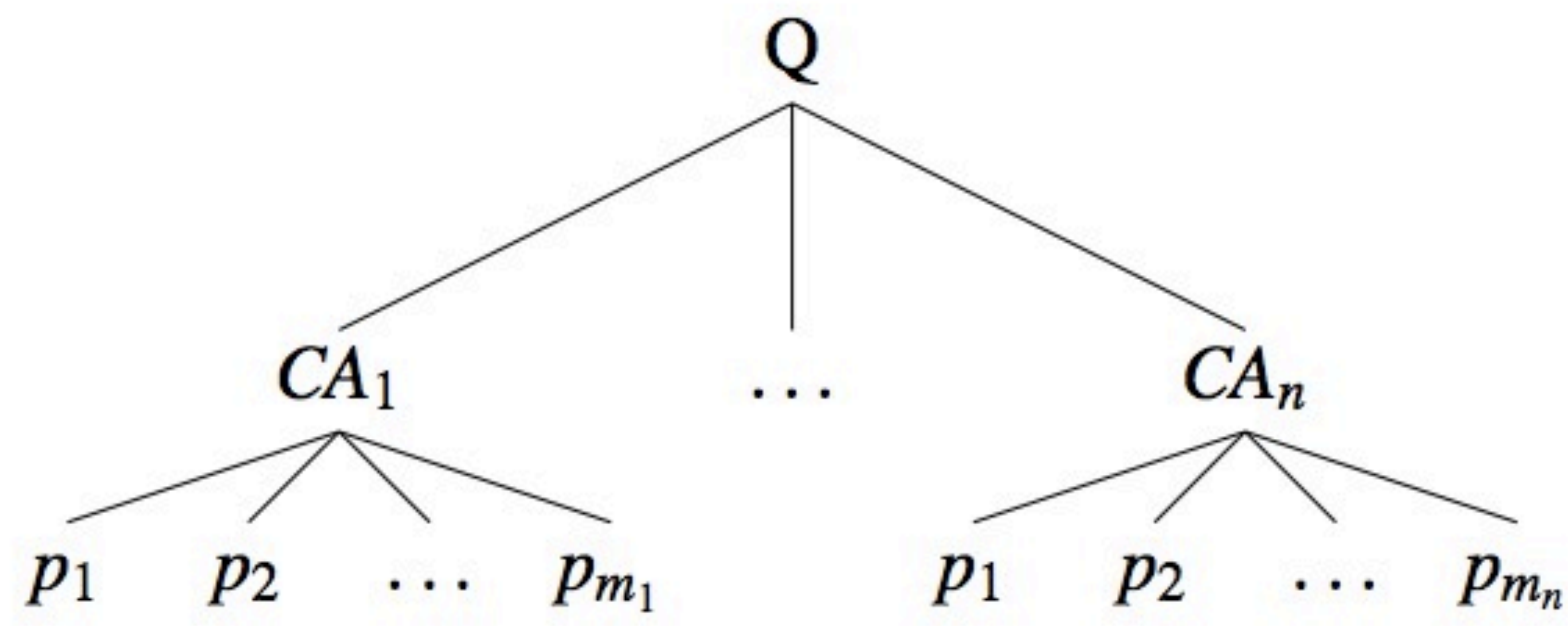
-- Watson tries to find the best passage that supports the answer

-- But all the information may not be present in one passage

-- In this work we present a framework to overcome this limitation

Question Answering Set-up



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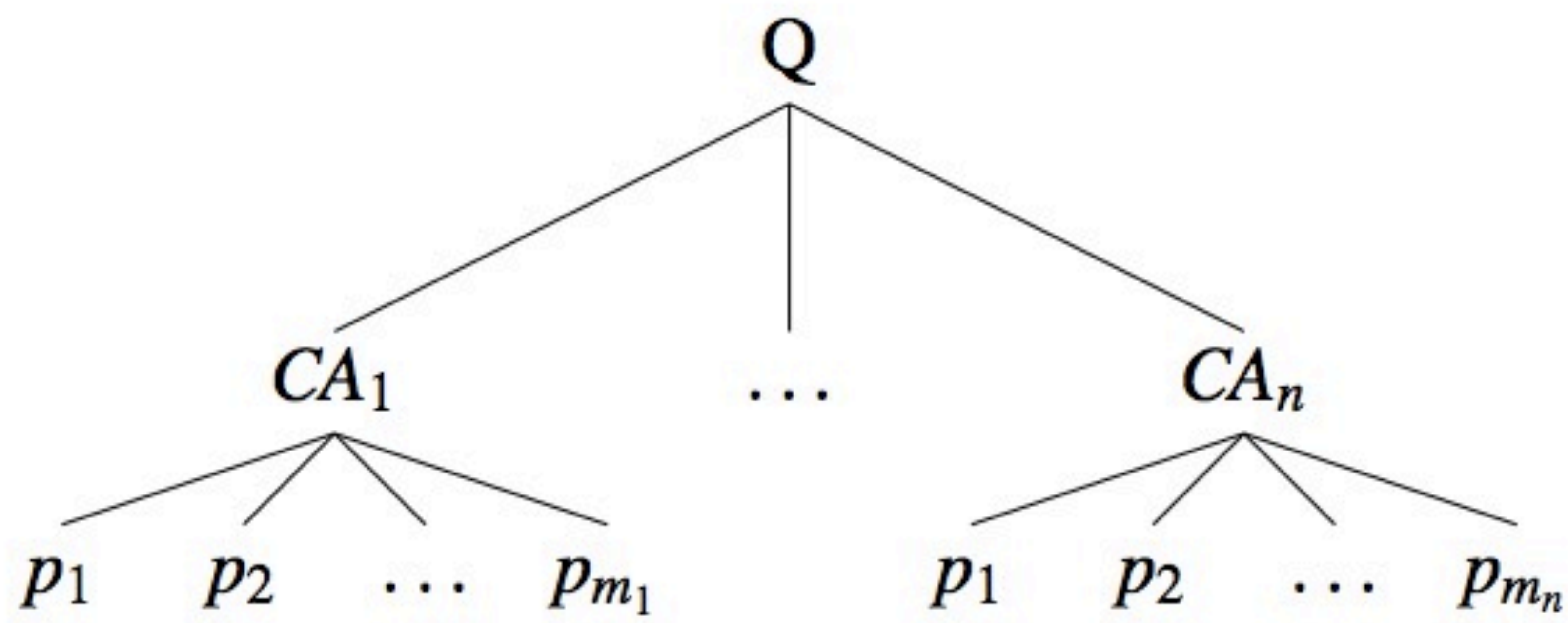


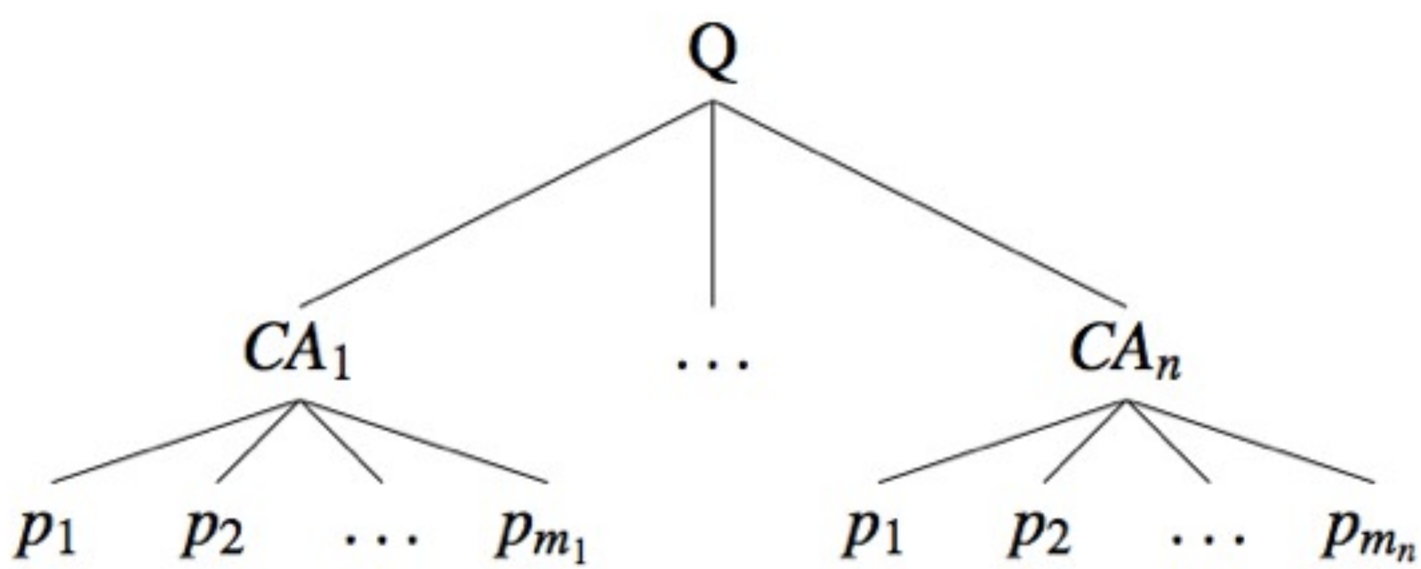
$$< Q_1, CA_1, -1 >, < Q_1, CA_2, -1 >, \ldots, < Q_1, CA_i, 1 >, \ldots, < Q_1, CA_{n_1}, -1 >$$

$$< Q_2, CA_1, -1 >, < Q_2, CA_2, -1 >, \ldots, < Q_2, CA_j, 1 >, \ldots, < Q_2, CA_{n_2}, -1 >$$

$$\ldots$$

$$< Q_m, CA_1, -1 >, < Q_m, CA_2, -1 >, \ldots, < Q_m, CA_k, 1 >, \ldots, < Q_m, CA_{n_m}, -1 >$$

Outline



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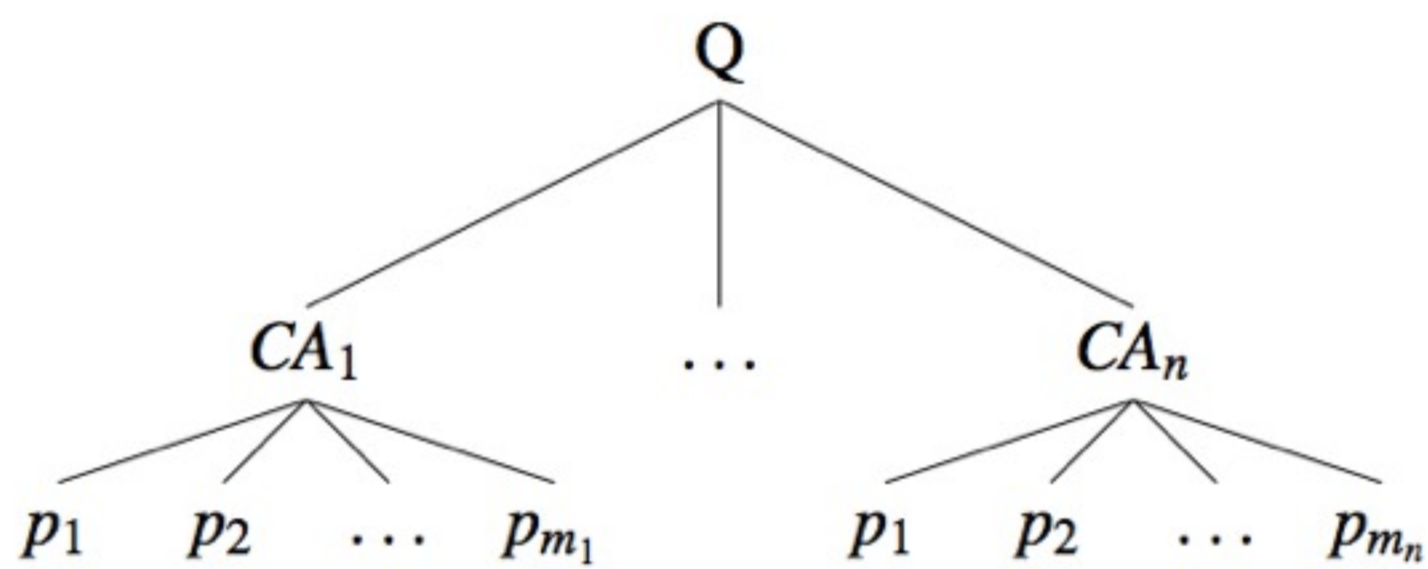
1. Brief overview of passage scorers in the system



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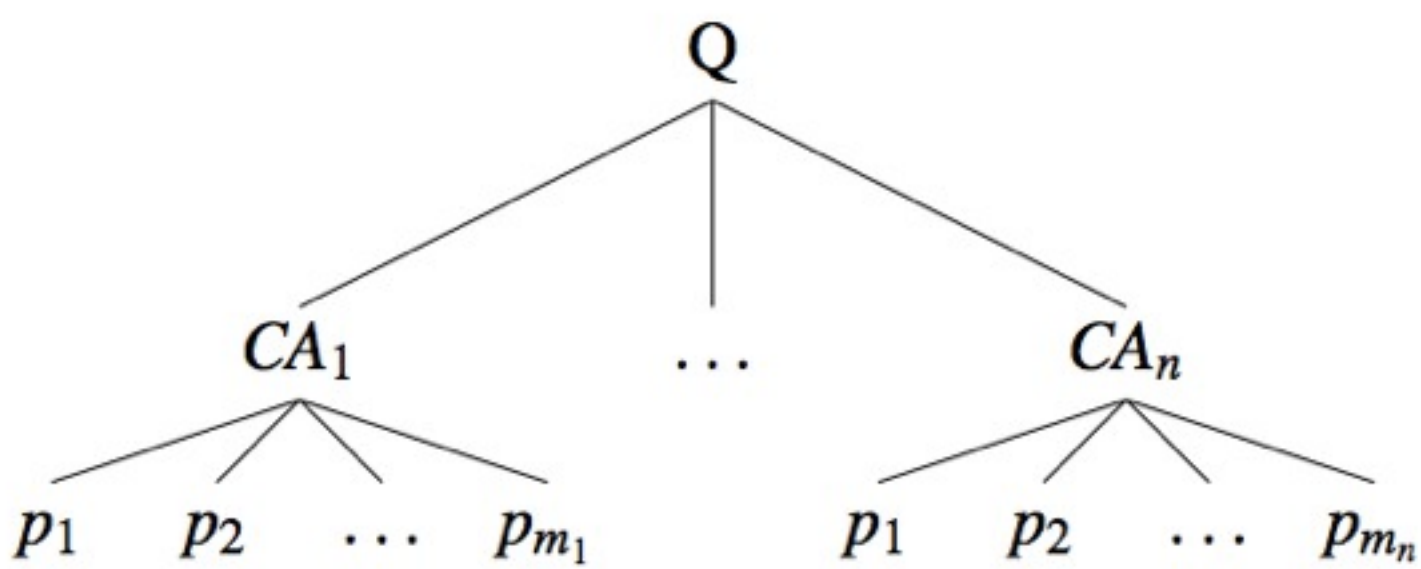
2. How features produced by passage scorers per passage are combined to get one feature for a candidate -- feature merger



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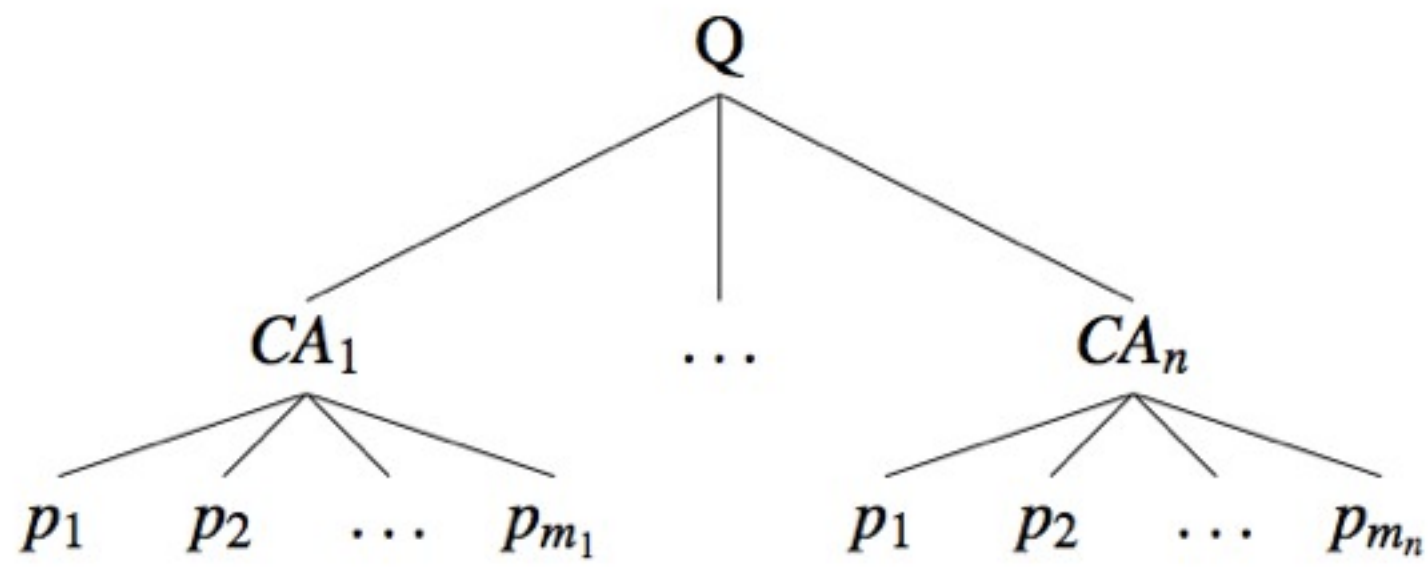

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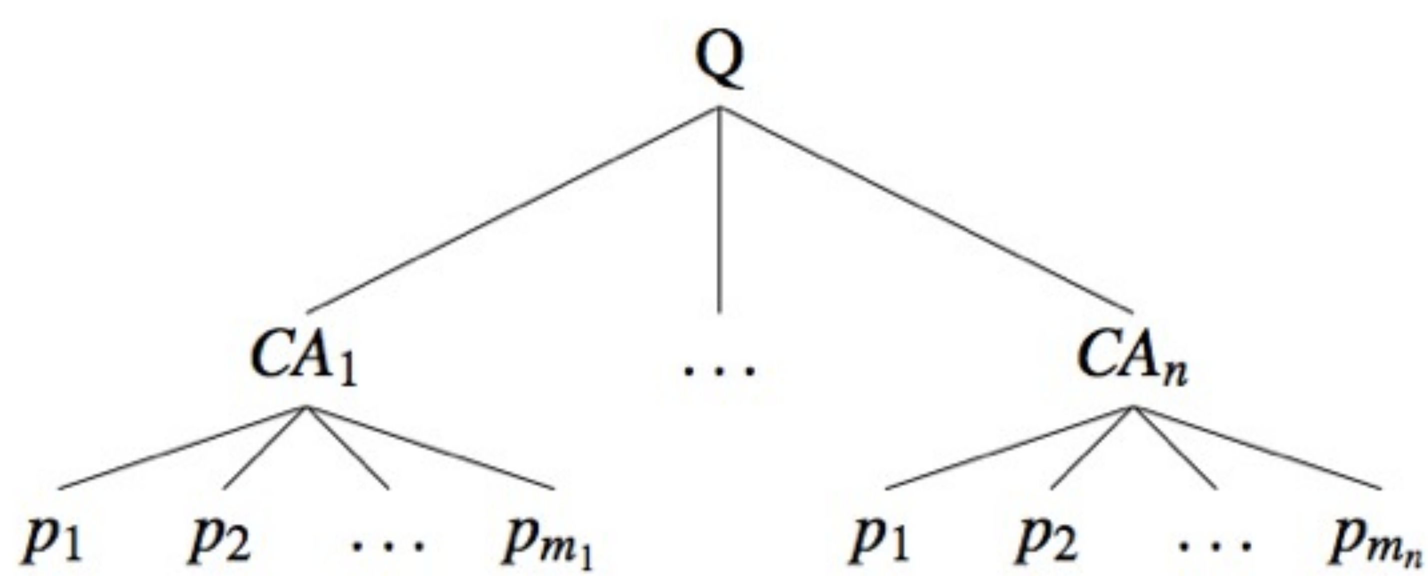
4. Experiments and results



Passage Scoring Features

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1. Capture how well Question matches supporting passages

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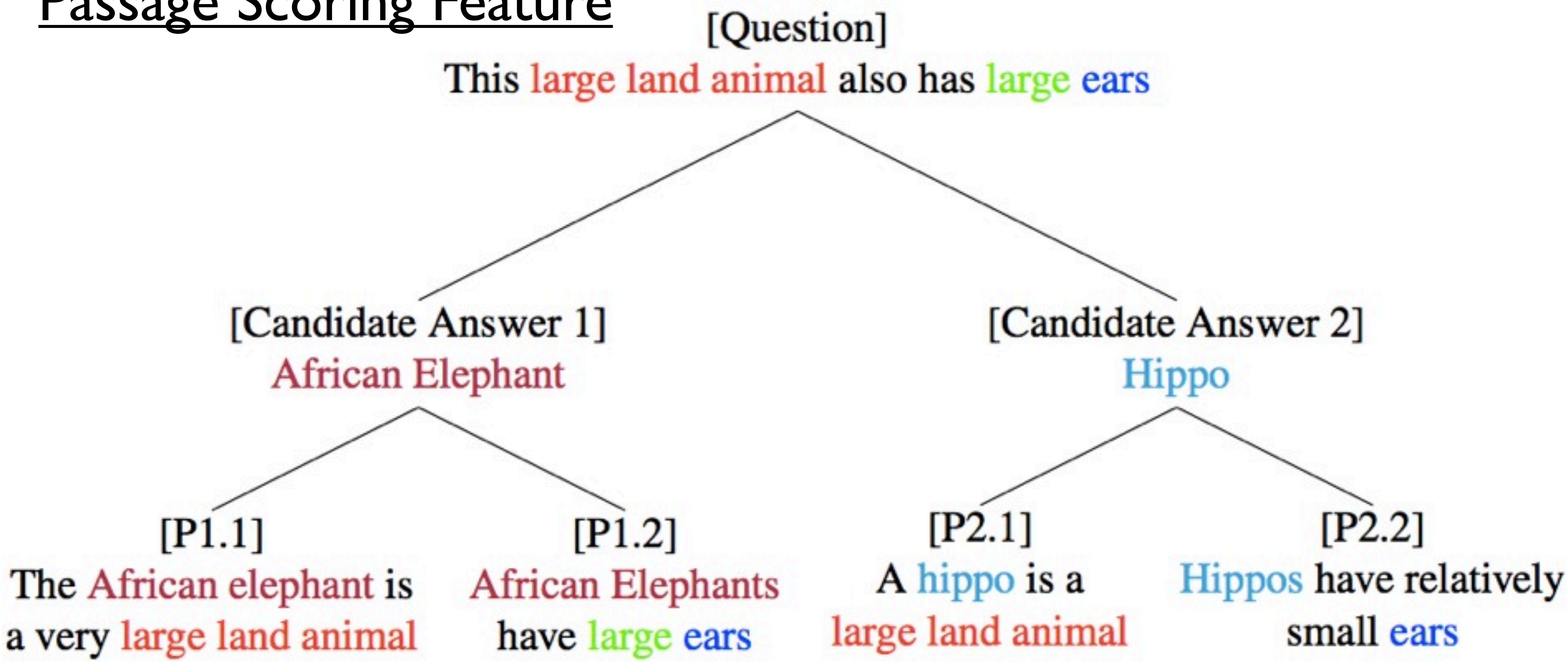
   d. **Logical Form Answer Candidate Scorer (LFACS)**: Targets high-precision matching between the syntactic structures of passages and questions.

Passage Scoring Feature



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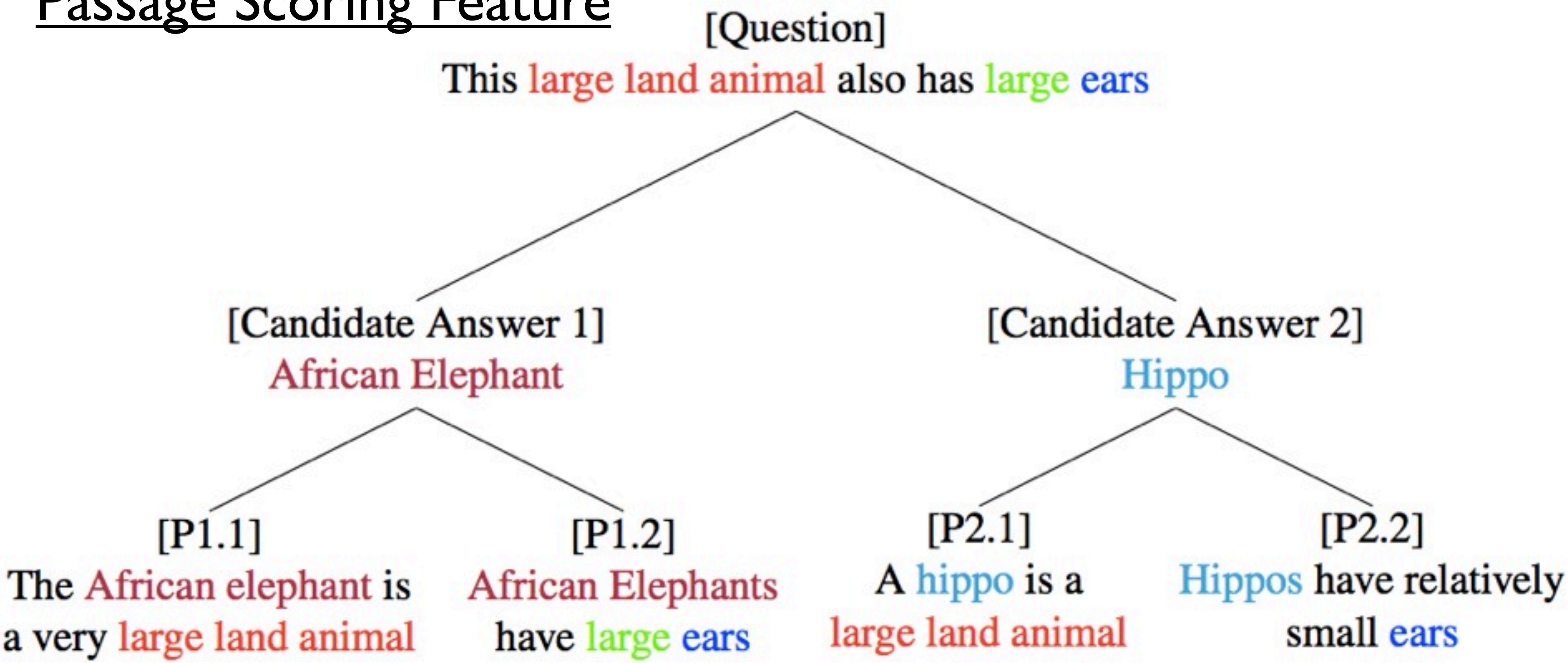
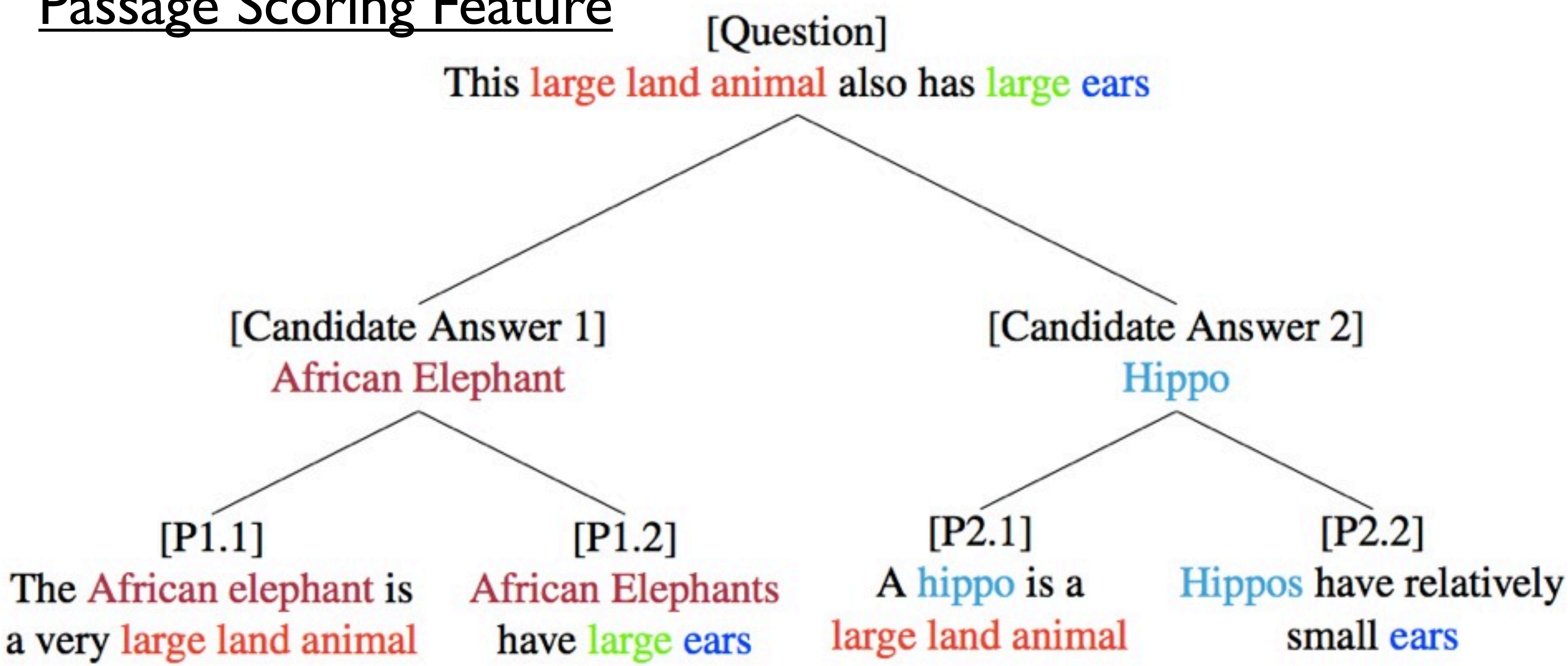


Elephant	large	land	animal	large	ears
P1.1	1	1	1	0	0
P1.2	0.0	0.0	0.0	1	1

Passage Scoring Feature



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$$f = \max_i \left(\sum_j^N a_{i,j} \right)$$

Other Merger Strategies

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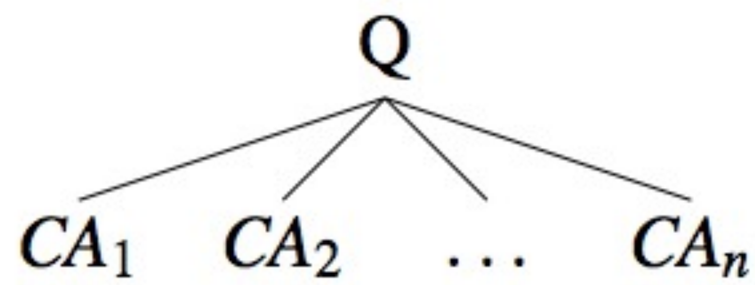
Our contribution: Introduce a framework to capture the distribution of this matrix.

More Formally...



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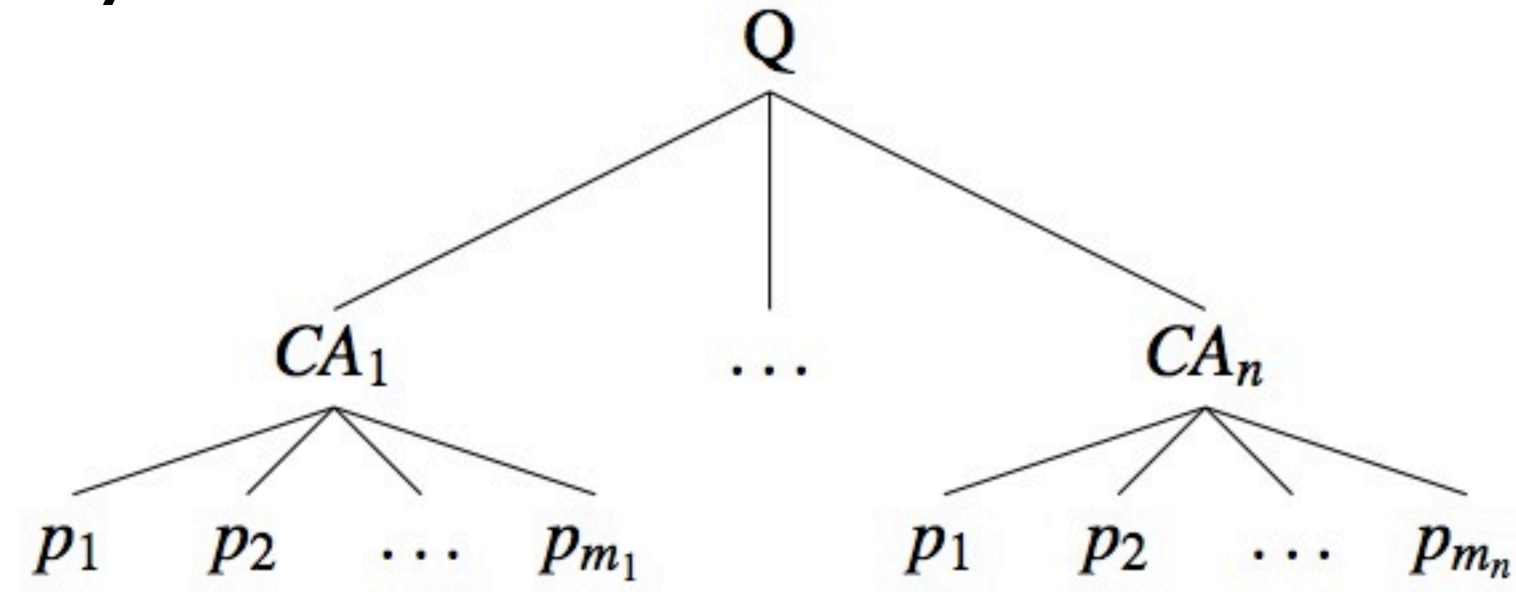

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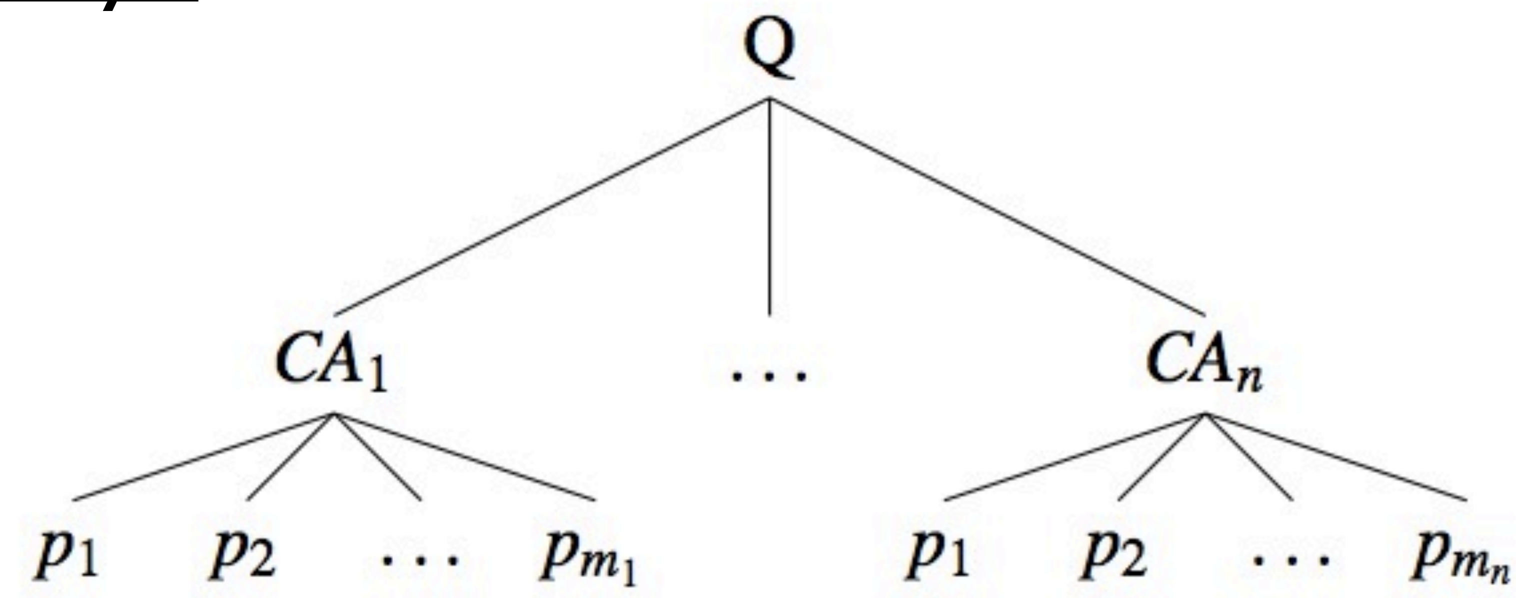
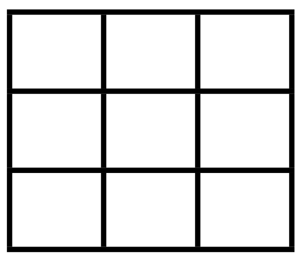


Question terms

Supporting passages



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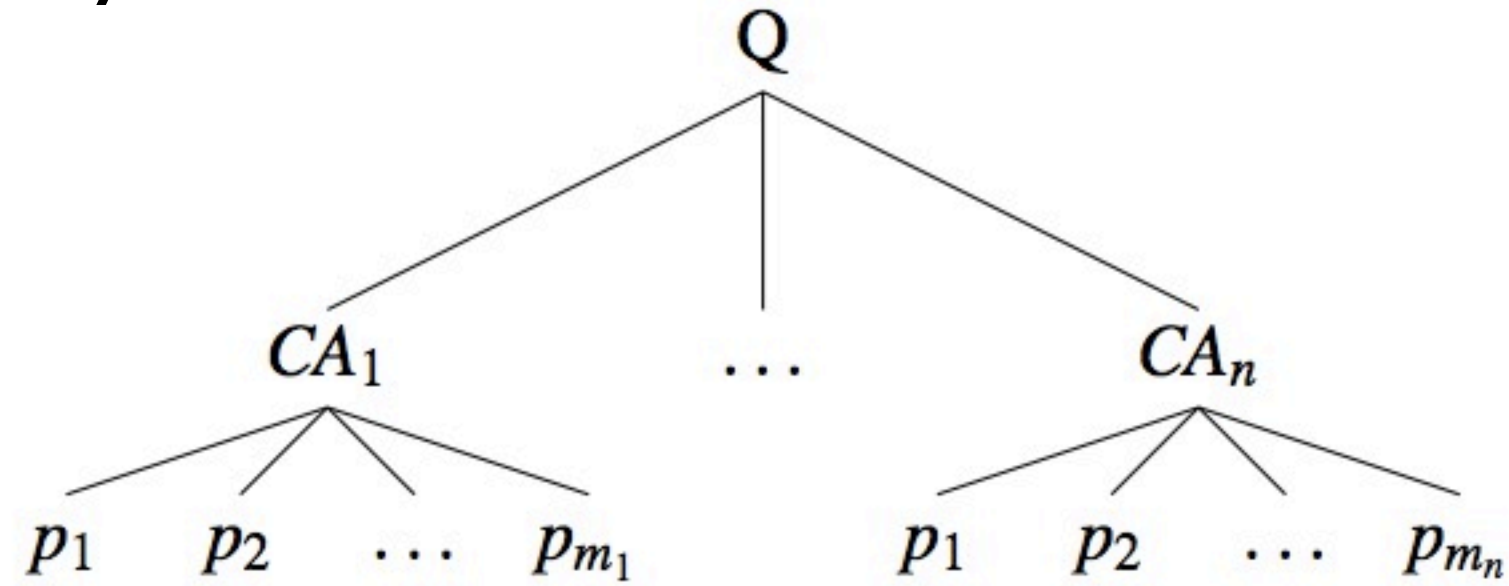

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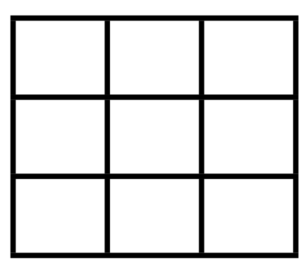

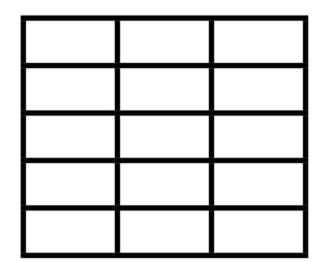

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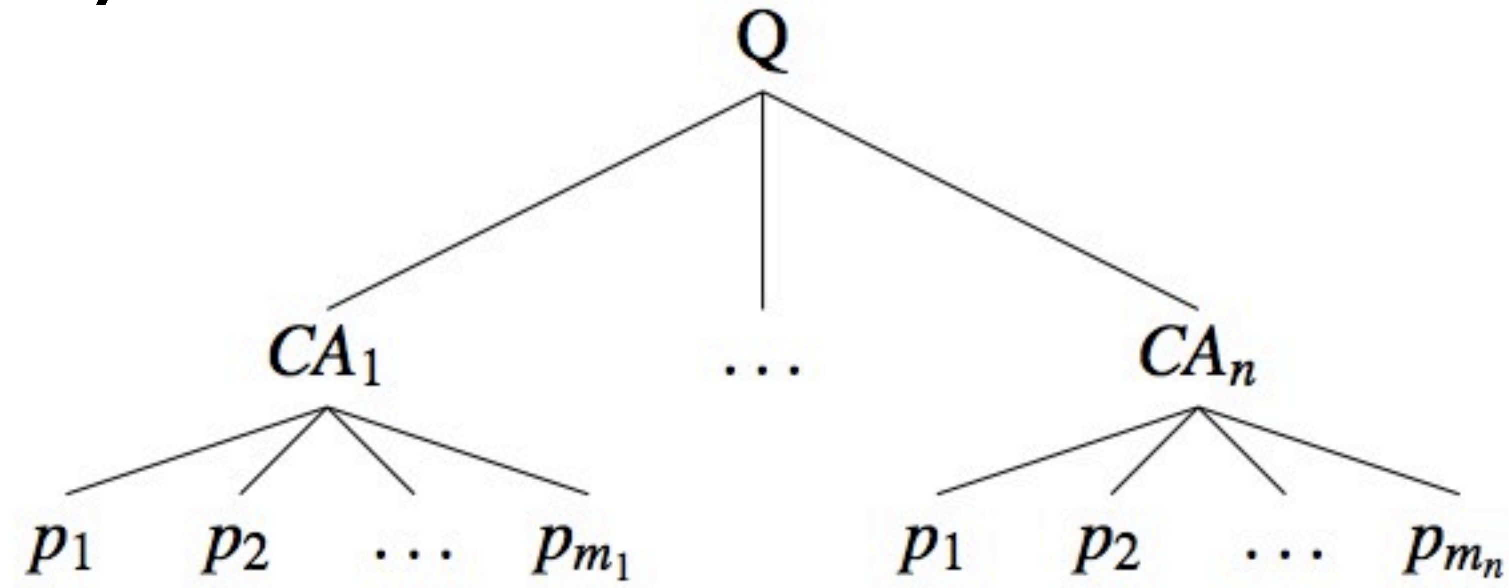

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Question 2

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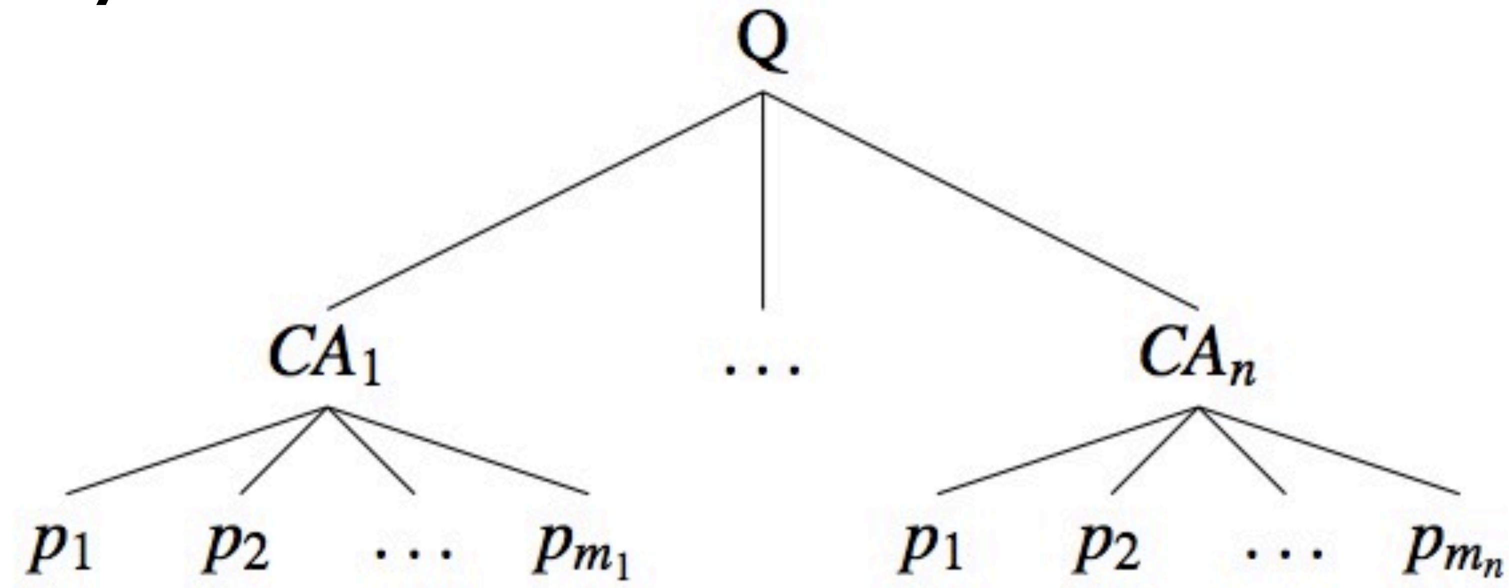

Question terms

Supporting passages

Question 1

Question 2

Cannot simply linearize this matrix

Multi-dimensional Feature Merger (MDM Features)

M =

	q1	q2	q3	q4	q5
p1					
p2					
p3					
p4					

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Introduce features that capture the distribution of this matrix

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$$g(M) =< sum(S), avg(S), std(S), max(S), min(S), dim(S), non{-}zero(S) >$$

Performance of new features

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Metrics:

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1. Correlation with the gold class in the training data

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Eg: CARDIOLOGY: Murmur associated with this condition is harsh, systolic, diamond-shaped, and increases in intensity with Valsalva

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(A: Hypertrophic cardiomyopathy)

Distribution of data-sets

Training	#Q	#Pos	#Neg	#Avg cand per Q
Jeopardy!	11,520	12,173	2,555,396	222.87
DD	1,322	2,338	543,963	413.23

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Test Data:

1. Jeopardy! 3,505

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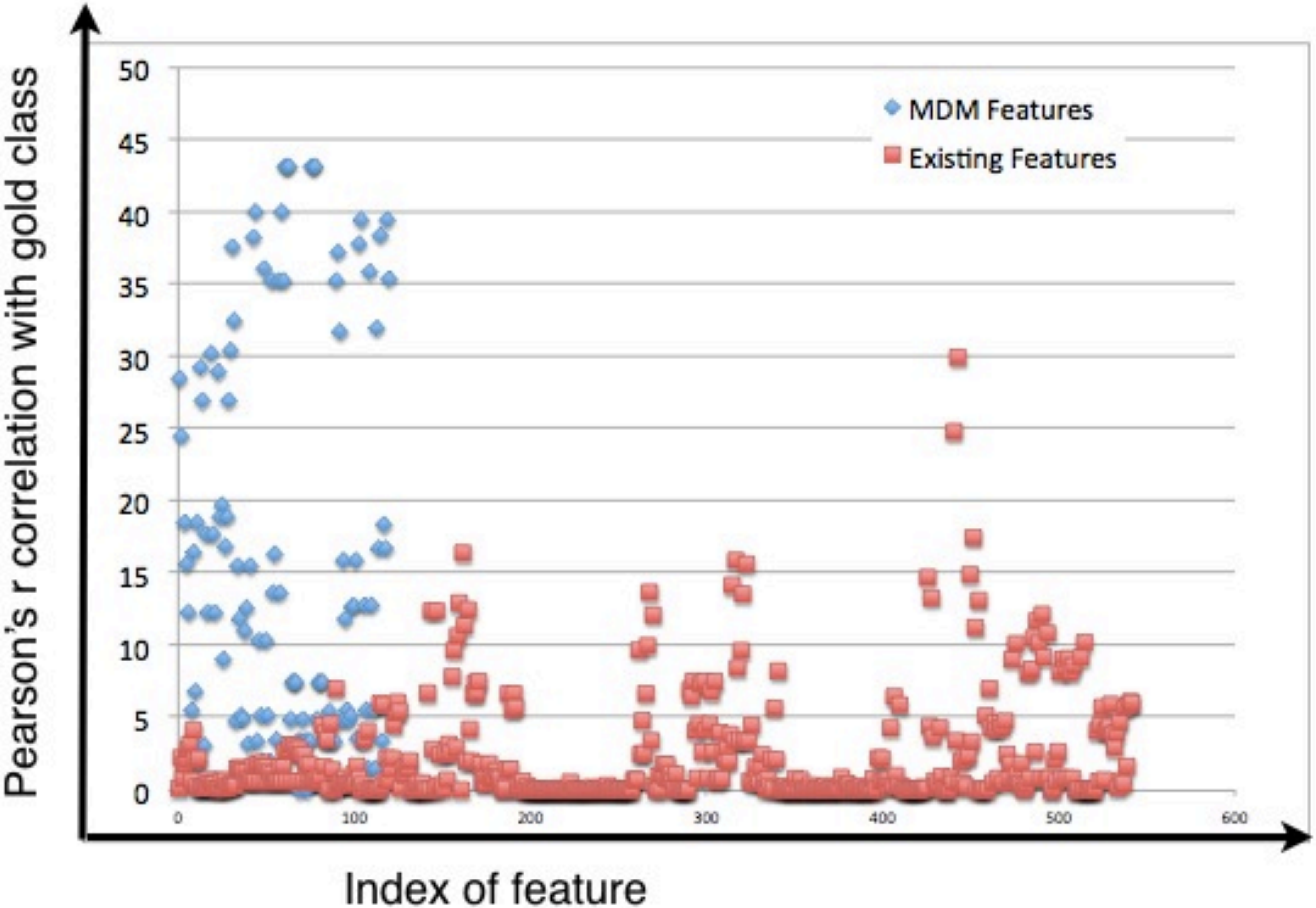
DD	1,322	2,338	543,963	413.23

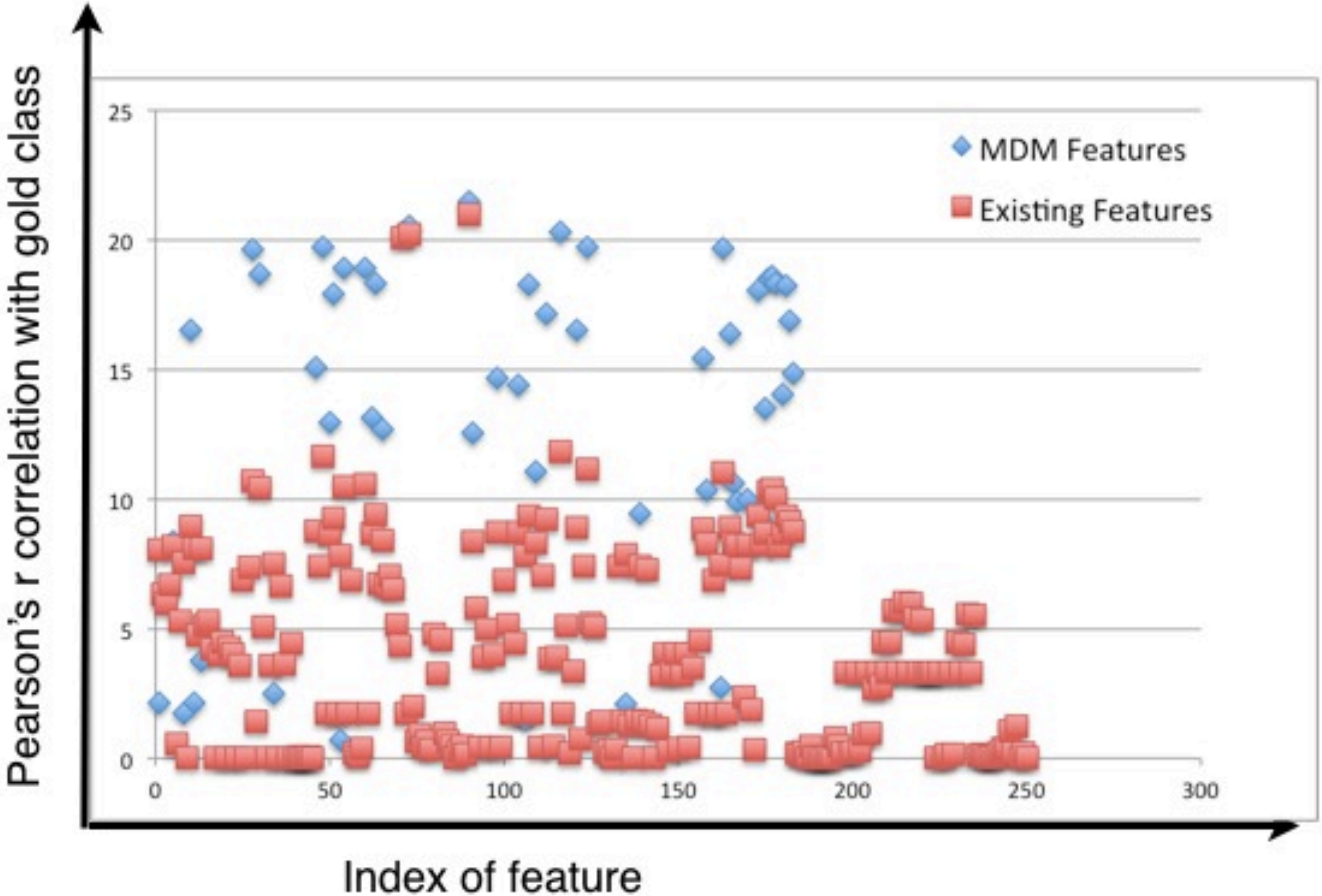
Test Data:

1. Jeopardy! 3,505
2. DD 905

Correlation with the gold class (Jeopardy!)



Correlation with the gold class (DD)



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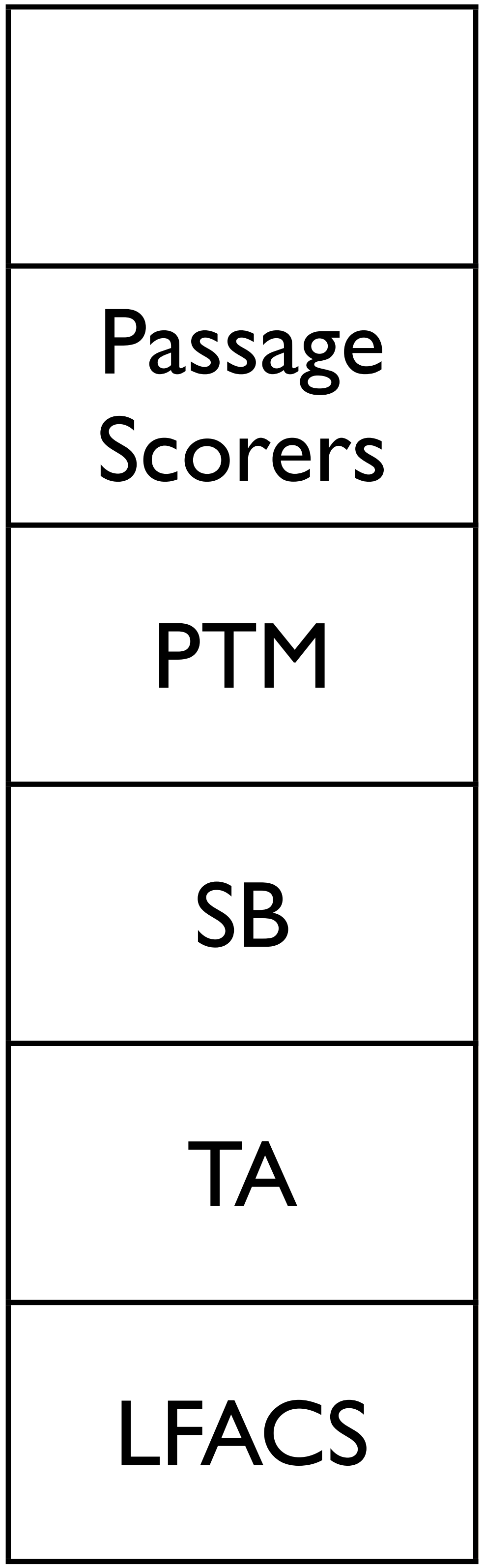

Component Level Analysis (DD)

	Component Level Baseline
Passage Scorers	Prec@70%
PTM	24.9
SB	26.8
TA	22.9
LFACS	25.7

Component Level Analysis (DD)

	Component Level Baseline	
Passage Scorers	Prec@70%	%Acc
PTM	24.9	20.2
SB	26.8	21.5
TA	22.9	18.8
LFACS	25.7	20.3

Component Level Analysis (DD)

	Component Level Baseline		With MDM
Passage Scorers	Prec@70%	%Acc	Prec@70%
PTM	24.9	20.2	29.2
SB	26.8	21.5	28.7
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Component Level Analysis (DD)

	Component Level Baseline		With MDM	
Passage Scorers	Prec@70%	%Acc	Prec@70%	%Acc
PTM	24.9	20.2	29.2	23.4
SB	26.8	21.5	28.7	23.3
TA	22.9	18.8	25.7	21.1
LFACS	25.7	20.3	28.5	22.4

End-to-end Analysis (DD)

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Baseline
Prec@70%
37.2

End-to-end Analysis (DD)

Baseline	
Prec@70%	%Acc
37.2	29.2

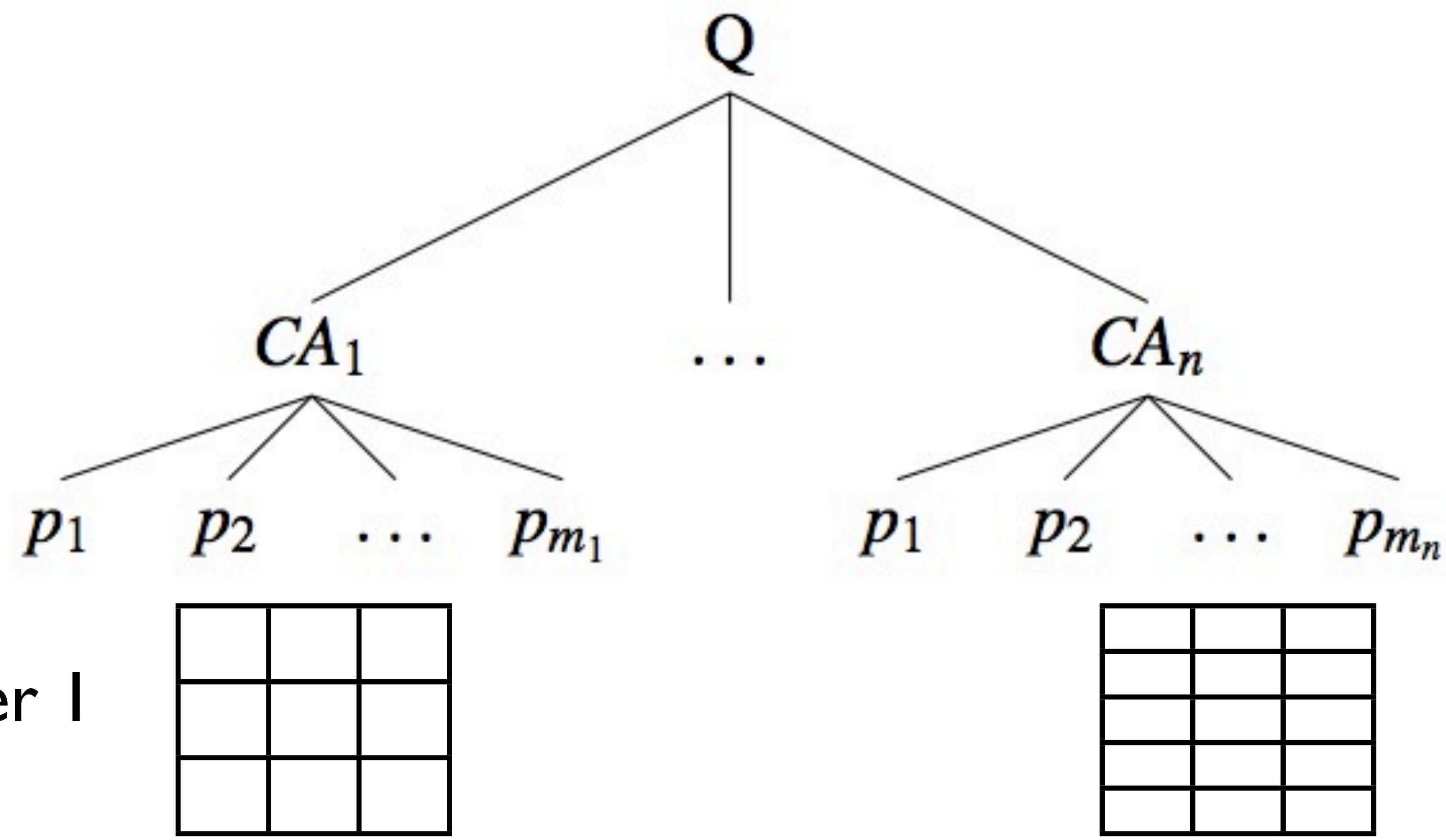
End-to-end Analysis (DD)

Baseline		With MDM
Prec@70%	%Acc	Prec@70%
37.2	29.2	40.2

End-to-end Analysis (DD)

Baseline		With MDM	
Prec@70%	%Acc	Prec@70%	%Acc
37.2	29.2	40.2	31.3

Why the heck is it called Multi-dimensional?



Passage scorer 1

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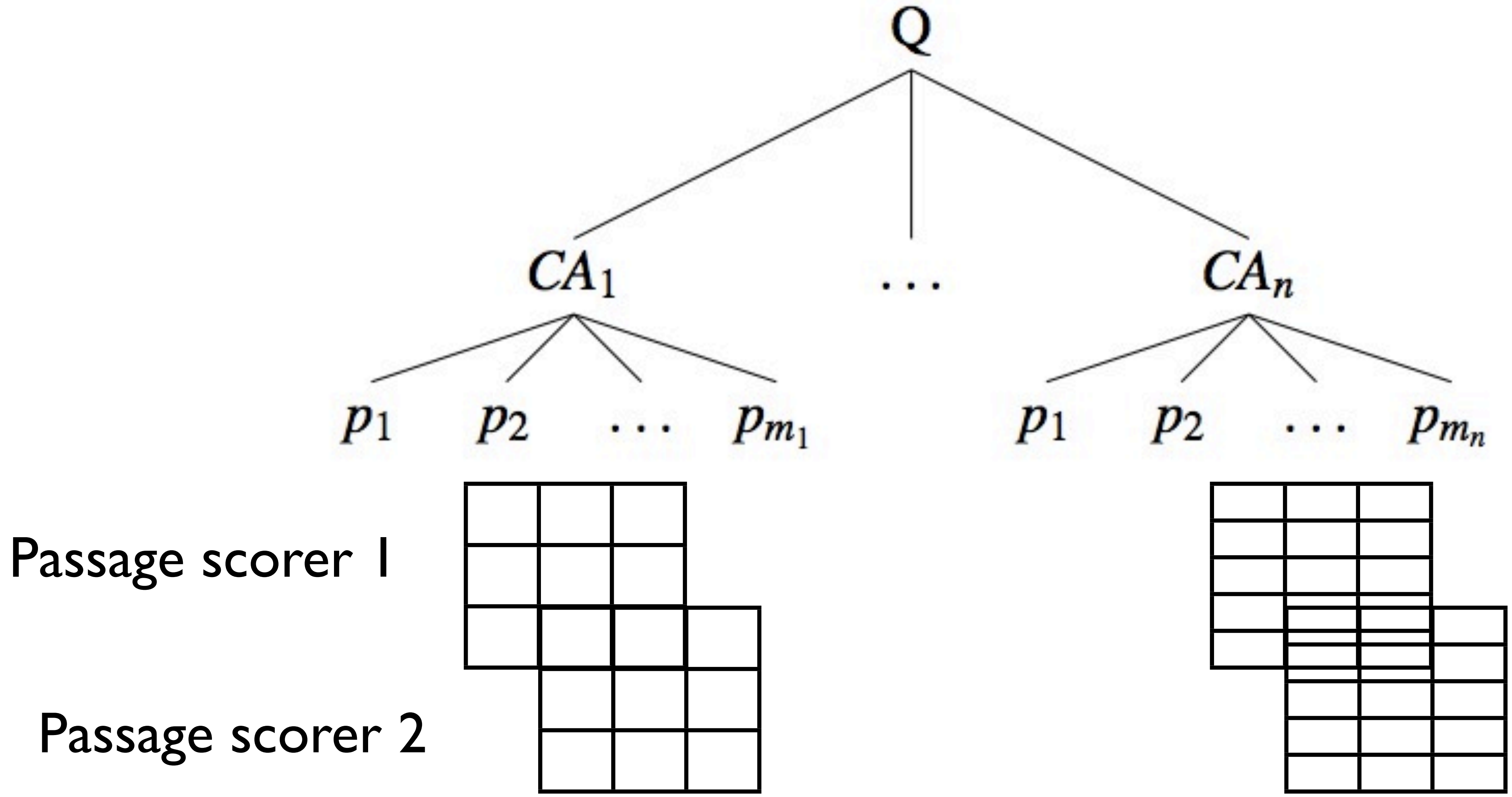

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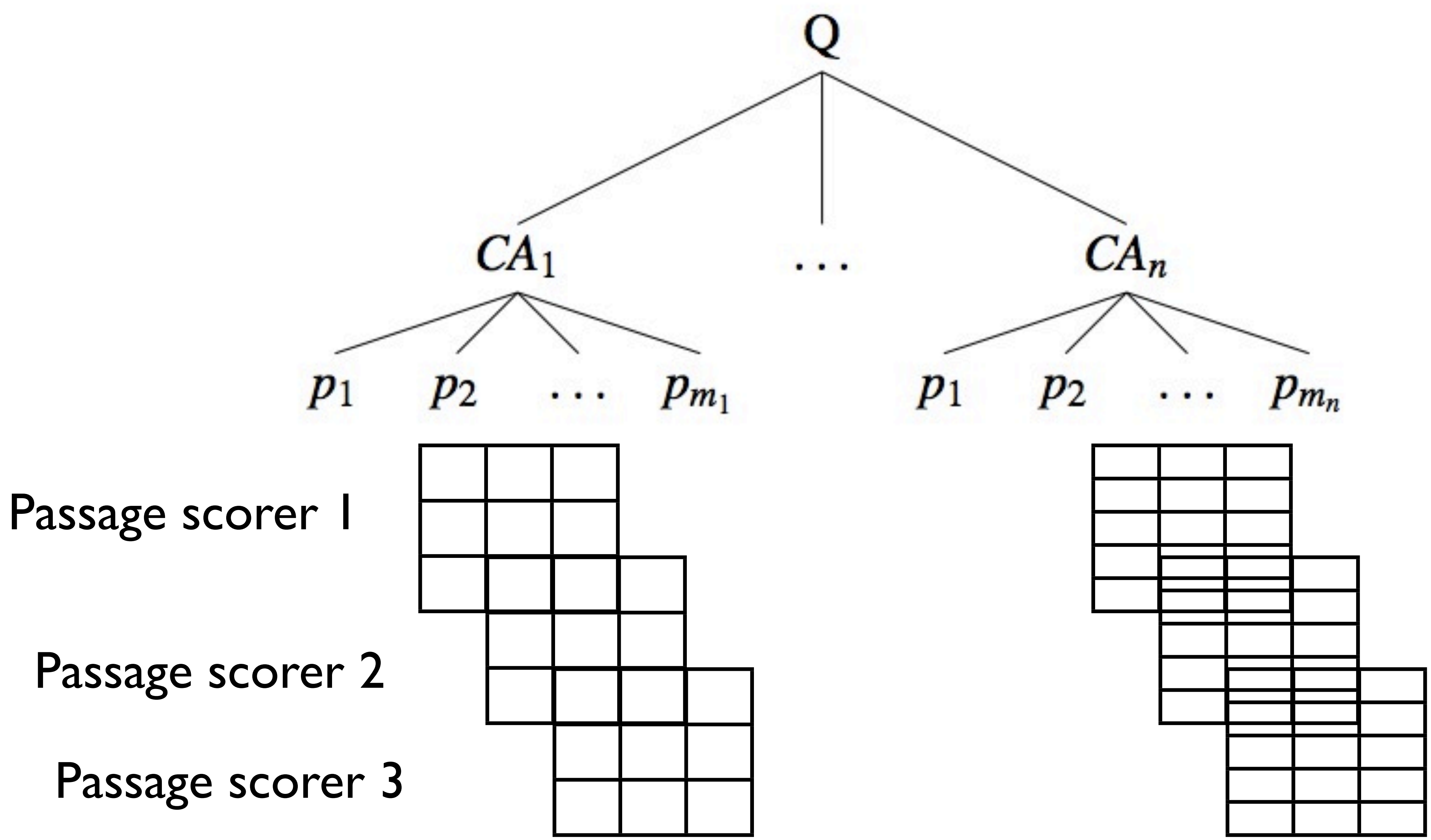

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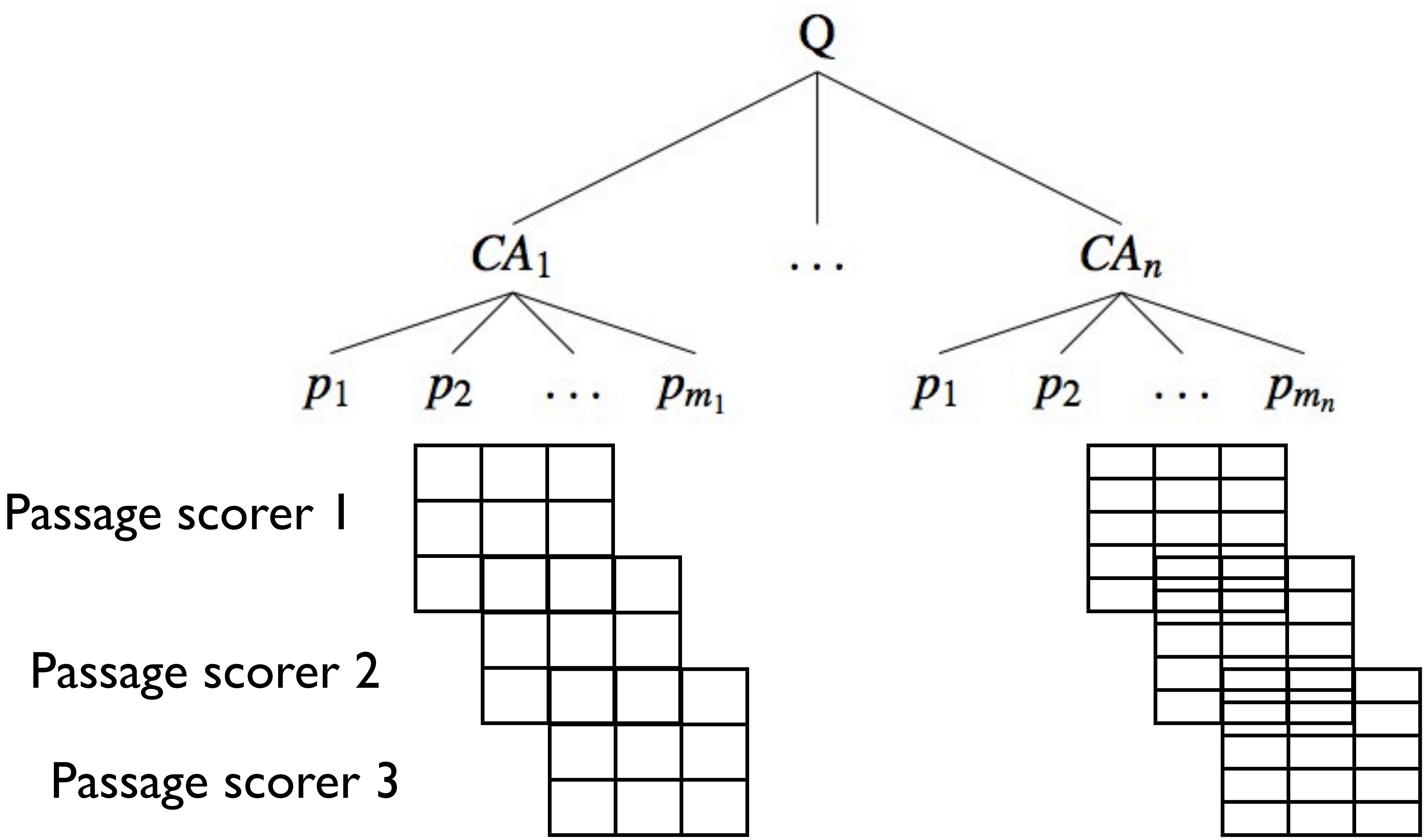

Future Work!

Conclusion

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Thanks and Questions?