Sentence Salience Classification Using Linguistic and Semantic Features in QA Systems

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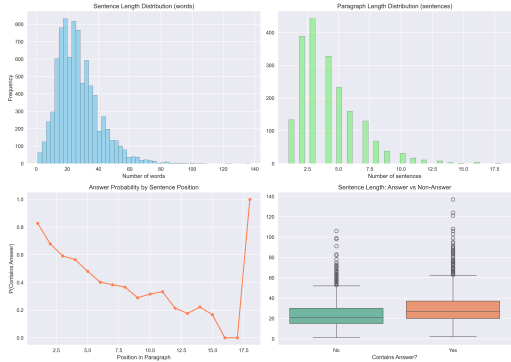
https://github.com/MadduruNikhil-IIITH/Squad-Salience-Sentence-Detection

"How can linguistic and semantic features such as word length, number of POS tags, sentence position, and surprisal estimations be extracted and utilized to enhance sentence salience classification in question-answering systems?"

Dataset — SQuAD v1.1 Training Set

- Source: SQuAD v1.1 **training set**
- Total passages: **19,035**
- Sampled: **2,000 passages**
- Total sentences: **8,328**
- Answer sentences: **5,178** (62.17%)



Class Imbalance in the Data

Observation

With 2,000 passages: **62.17% Answer sentences** → moderate positive skew Smaller samples (e.g. 100 passages) can exceed 70–75% → severe imbalance

All 26 Features

Original Proposal Category	Actual Features Implemented (26 total)
Surface features	sentence_length_words sentence_position sentence_position_norm
Lexical features	type_token_ratio lexical_density
POS-based features	noun_ratio, verb_ratio adj_ratio, pronoun_ratio
Discourse features	causal_marker_ratio contrast_marker_ratio named_entity_density
Surprisal (GPU/CUDA) — GPT-2	gpt2_surprisal_mean, sum, std gpt2_surprisal_var, min, max
Surprisal (GPU/CUDA) — BERT	bert_surprisal_mean, sum, std bert_surprisal_var, min, max

Methodology & Final Results

- Model: Logistic Regression (`class_weight='balanced'`)
- Split: 80/20 stratified
- Main run: 2,000 passages

Final Performance

Metric	Score
Accuracy	**69.27%**
F1	**0.7377**
Precision	**0.7860**
Recall	**0.6950**

Ablation

Top-10 features only → 68.29% accuracy, 0.7360 F1, 0.7648 Precision, 0.6873 Recall
No Suprisal features → 69.21% accuracy, **0.7416** F1, 0.7756 Precision, **0.7104** Recall

Top 10 Most Predictive Features

Rank	Feature	Coefficient
1	sentence_position	**-0.796**
2	gpt2_surprisal_sum	+0.663
3	gpt2_surprisal_var	-0.444
4	bert_surprisal_std	+0.364
5	noun_ratio	+0.331
6	bert_surprisal_var	-0.315
7	named_entity_density	+0.298
8	gpt2_surprisal_std	+0.283
9	sentence_position_norm	+0.257
10	lexical_density	-0.256

Performance Scaling

Passages	Sentences	Answer %	Accuracy	F1
100	577	73.5%	70.7%	0.793
500	2,277	68.3%	66.0%	0.740
1,000	4,485	63.8%	69.1%	0.748
2,000	**8,328**	**62.2%**	**69.3%**	**0.738**

Ablation Study — The Surprising Truth

Passages	Full Model	No Surprisal	Top-10
100	70.69% / 79.27%	67.24% / 75.95%	66.38% / 76.07%
250	63.31% / 70.93%	**67.74% / 75.16%**	64.11% / 71.20%
500	66.01% / 74.04%	65.57% / 73.43%	65.57% / 73.61%
1,000	69.12% / 74.80%	67.00% / 72.79%	66.78% / 72.76%
2,000	69.27% / 73.77%	**69.21% / 74.16%**	67.41% / 72.39%

(Accuracy / F1 %). Bold = best per row.

Future Work — Including Class Imbalance Handling

Planned Extensions

- **Semantic Role Labeling (SRL)** — AllenNLP
- **Rhetorical Structure Theory (RST)** annotations
- Question–sentence dependency paths
- Coreference resolution features.

Specific Focus on Class Imbalance

- Future:
  - Undersampling / oversampling (SMOTE, NearMiss)
  - Cost-sensitive learning with dynamic weights

These improvements + discourse features expected to push $F1 > 0.80$

Conclusion

Yes — hand-crafted features are highly effective!

- Achieved **69.3% accuracy** and **0.738 F1** using only linguistic + surprisal features.
- **Sentence_position** is the dominant signal — answers overwhelmingly appear in the first few sentences of SQuAD paragraphs.
- No BERT embeddings or neural encoders used.
- Despite large positive coefficients for GPT-2 surprisal features, removing all 12 surprisal features **improved performance**.
- The counter-intuitive result is due to **multicollinearity**: surprisal is highly correlated with linguistic features, introducing noise in linear models.
- Strong foundation for SRL, RST, and advanced imbalance handling.

Thank You

Questions?