# WebNLG Challenge 2019 - Phase 2

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# Overview of Presentation

1. Project Philosophy and Ideas
2. Phase A - (40 models)
    a. Overview and Results
3. Vocab Generation Overview for Phase B
4. Phase B - (60 models)
    a. Overview and Results
5. Phase C - (64 models)
    a. Overview and Results
6. Final Results
7. Future Work

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    - Further refined parsing methods and ideas
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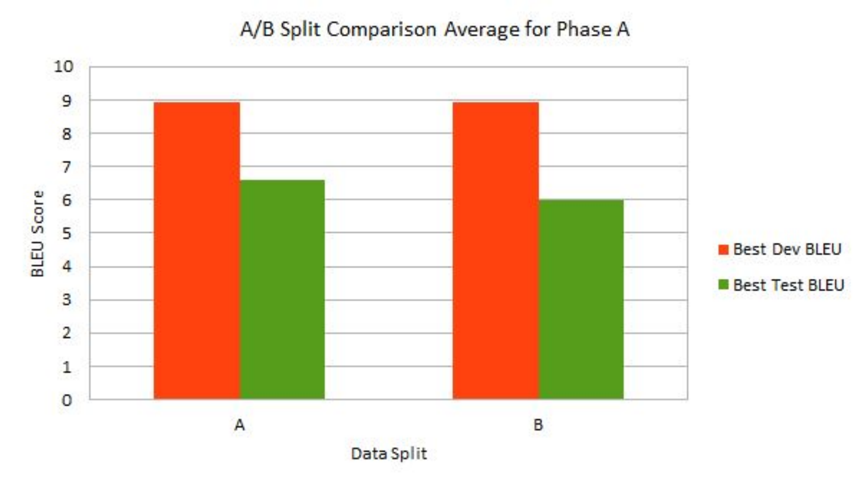
  - Each phase has a fundamentally different approach to the problem, but utilizes and carries the best models from the prior phase
- Picked the best
  - Tested over 170 models!

# Train/Test Split - Phase A

- Data was split two ways
  - A = 10% dev, 80% train, 10% test
  - B = 10% dev, 85% train, 5% test
- Split was done by iterating over entries and maintaining a count of modulo 20, with specific values assigned to either set.
- This ensured that A.Dev, A.Test, B.Dev and B.Test had no overlap.
- After Phase A, split A and B were close and were carried into testing for Phase B



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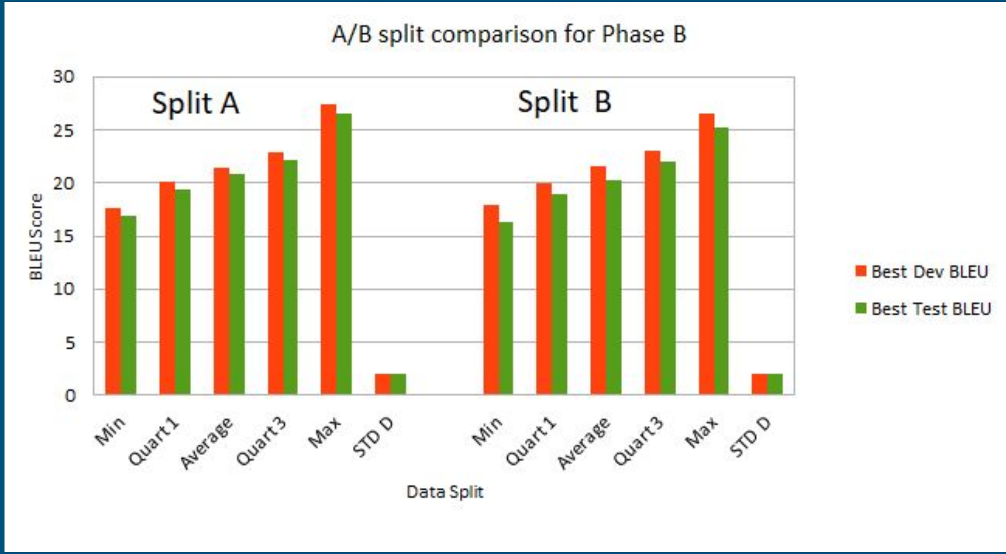
- The SPACE SPLIT method yielded the best BLEU score surprisingly. RDF vocab generation was trivial.

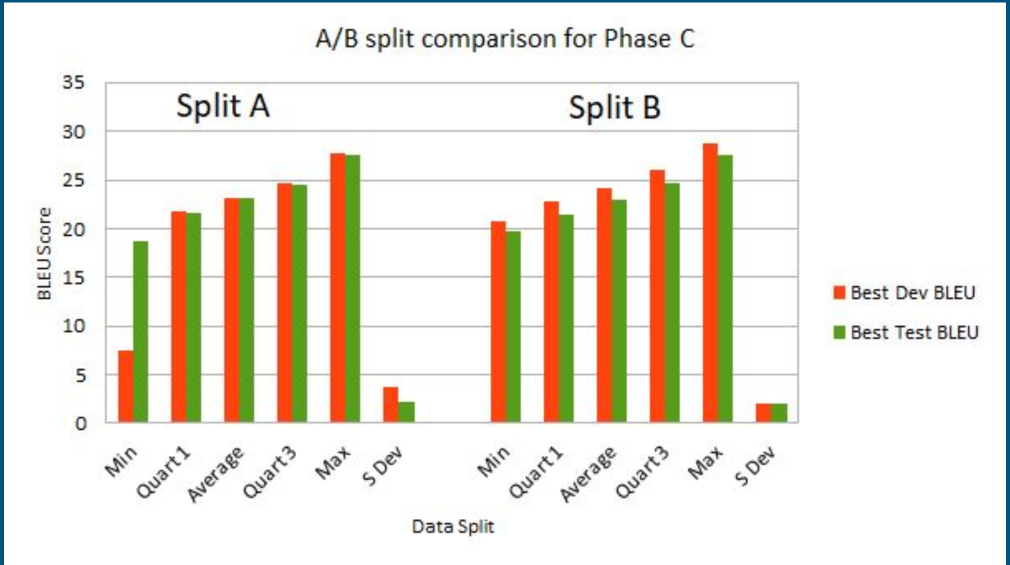
# Train/Test Split - Phase B

- In Phase B, split A and B were paired with vocab 0 to 4 and tested a total of 60 times. The results were compared and split B was slightly ahead of split A by an average value of .5 BLEU score.
- The top two models advanced to Phase C, which were V0-A and V0-B



# Train/Test Split - Phase C

- In phase C, the data was again very similar but for larger models B pulled ahead. Split A had poor performance in some of the more complex models leading to drastically reduced minimum scores.
- This leaves B as the prefered data split.



# Models - Phase B/C

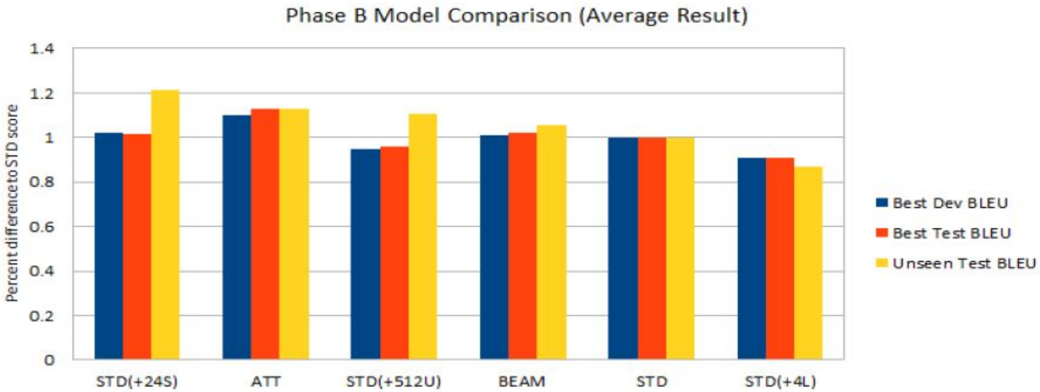
Phase B

- Tier 0: Base model
    - Test: 20.43, (None changed)
- Tier 1: One param changed
    - Max Test, 23.07 (ATT)

Phase C

- Tier 2: Two params changed
    - Max Test. 26.8 (ATT,24S)
- Tier 3: Three params changed
    - Max Test. 27.6 (BEAM,ATT,24S)
- Tier 4: Four params changed
    - Max test, 26.8 (BEAM,ATT,24S,512U)
- Tier 5: All params changed
    - Max test, 23.7 (All changed)

| Key % | Model (Avg) | Dev Perplexity | Best Dev BLEU | Test Perplexity | Best Test BLEU | Unseen Test |
|---|---|---|---|---|---|---|
| 1st | STD(+24S) | 109.16% | 102.36% | 110.34% | 101.52% | 121.09% |
| 2nd | ATT | 91.41% | 109.77% | 91.80% | 112.92% | 112.75% |
| 3rd | STD(+512U) | 123.37% | 94.77% | 123.23% | 95.79% | 110.90% |
| 4th | BEAM | 99.98% | 100.79% | 99.48% | 102.25% | 105.78% |
| 5th | STD | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |
| 6th | STD(+4L) | 109.53% | 90.83% | 113.35% | 90.80% | 87.02% |



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- Model with beam search, attention-mechanism, 24,000 steps and 512 units.
- Need to make this model ‘better’ in terms of generalized predictions

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- Delexicalization means replacement of specific words, both in lex and triples, with the category it is associated with.
- *'Name | loves | Country'* and *'Name | speaks | Language'*

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- Goal is to define categories which groups as many words as possible in itself

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- Astronauts : list of all the names of astronauts was made from Wikipedia and all the occurrences of names of astronauts were replaced by the keyword 'ASTRONAUT'.

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- Q: Isn’t delex is supposed to boost the scores?
- A: With more and more categories expressed, less expressive sentences are generated (Bleu score ratio will decrease) (Re-lexicalization Solution)

# Final Results

| Team | Bleu Score |
|---|---|
| **Our Model** | **46.2** |
| MELBOURNE | 45.13 |
| TILB-SMT | 44.28 |
| PKUWRITER | 39.88 |
| UPF-FORGE | 38.65 |
| TILB-PIPELINE | 35.29 |
| TILB-NMT | 34.60 |
| BASELINE | 33.24 |
| ADAPT | 31.06 |
| UIT-VNU | 7.07 |

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- Choice of model (nmt/pipeline/smt) should depend on dataset
- Each phase from data preprocessing to selecting model parameters is as important as the other.