# Naïve Semantic Text Similarity Model

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# Outline

# Introduction

- Semantic Text Similarity (STS) is crucial for many NLP tasks
- Challenge: Which features best capture semantic similarity? [1]
- Our approach: Unbiased feature analysis using process pipeline permutations and Random Forests for feature analysis

# Methodology

- Approach
- Feature extraction
- Feature selection
- Model training
- Model evaluation

# Approach

- Naïve approach which requires no knowledge of the corpus
- Use categorized steps to process sentences in every permutation
  - 520 permutations
  - e.g. sentence_to_doc → `chunk_NEs` → `remove_stopwords` → `lemmatize_tokens` → `get_characters` → `get_2grams`
- Apply 4 similarity metrics to each permutation
  - Jaccard, Cosine, Euclidean, Manhattan
- Used Random Forest's feature importance capabilities
- Let the data guide feature selection

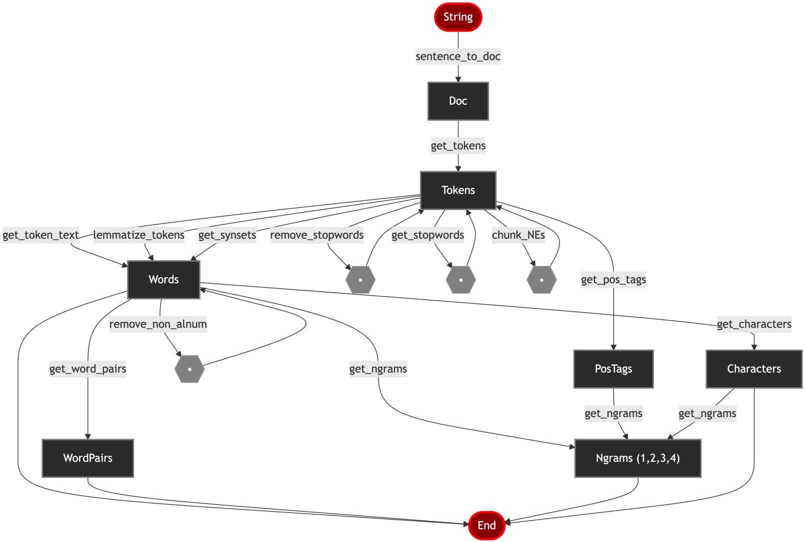
# Choosing Processing Steps

- Used steps from class such as Lemmatization, Named Entity Chunking, and POS Tagging
- Used the Jaccard similarity metric from class
- Also chose to add character extraction, n-grams and word pairs, based on the methodology of the UKP team [2]
- Added new metrics: Cosine, Euclidean, Manhattan distance, all based on vectorizing word membership

# Feature Extraction

Feature Extraction

# Feature Extraction



# generate_valid_permutations()

```python
# Generate all valid permutations of sentence processing steps
def generate_valid_permutations(
    functions: List[Callable] = all_functions,
) -> List[Tuple[Callable, ...]]:
    valid_permutations = []
    for n in range(1, len(functions) + 1):
        for perm in itertools.permutations(functions, n):
            if _is_valid_permutation(perm):
                valid_permutations.append(perm)
    # Add sentence_to_doc to the beginning of each permutation
    valid_permutations = (
        [tuple([sentence_to_doc]) + perm for perm in valid_permutations])
    # Add final step to each permutation (e.g. get_2grams)
    valid_permutations = (
        [new_perm for perm in valid_permutations for new_perm in add_final_step(perm)])
    return valid_permutations
```

```python
# Dictionary to hold function names and their input/output types
function_input_output_types: Dict[str, Tuple[Tuple[type, ...], type]] = {}

# Extract the input and output types of a function
def _extract_input_output_types(func: Callable) -> Tuple[type, type]:
    signature = inspect.signature(func)
    param_types = [param.annotation for param in signature.parameters.values()]
    return_type = signature.return_annotation
    return param_types[0], return_type

# Populate the dictionary with function names and their input/output types
for func in all_functions:
    input_types, output_type = _extract_input_output_types(func)
    function_input_output_types[func.__name__] = (input_types, output_type)


# Function to check if a permutation is valid based on input/output types
def _is_valid_permutation(perm: Tuple[Callable]) -> bool:
    if function_input_output_types[perm[0].__name__][0] != spacy.tokens.doc.Doc:
        return False
    if function_input_output_types[perm[-1].__name__][1] not in [
        Tuple[Word, ...],
        Tuple[PosTag, ...],
        Tuple[Character, ...],
    ]:
        return False
    for i in range(len(perm) - 1):
        _, current_func_output_type = function_input_output_types[perm[i].__name__]
        next_func_input_type, _ = function_input_output_types[perm[i + 1].__name__]
        if current_func_output_type != next_func_input_type:
            return False
    return True
```

```
class PosTag(str): pass
class Word(str): pass
class Character(str): pass
class Ngram(Tuple[Word | Character | PosTag, ...]): pass
class WordPair(Tuple[Word, Word]): pass

def get_characters(words: Tuple[Word, ...]) -> Tuple[Character, ...]:
def get_word_pairs(words: Tuple[Word, ...]) -> Tuple[WordPair, ...]:
def sentence_to_doc(sentence: str) -> spacy.tokens.doc.Doc:
def get_tokens(doc: spacy.tokens.doc.Doc) -> Tuple[spacy.tokens.token.Token, ...]:
def get_pos_tags(tokens: Tuple[spacy.tokens.token.Token, ...]) -> Tuple[PosTag, ...]:
def lemmatize_tokens(tokens: Tuple[spacy.tokens.token.Token, ...]) -> Tuple[Word, ...]:
def get_token_text(tokens: Tuple[spacy.tokens.token.Token, ...]) -> Tuple[Word, ...]:
def get_2grams(words: Tuple[Word | Character | PosTag, ...]) -> Tuple[Ngram, ...]:
def get_3grams(words: Tuple[Word | Character | PosTag, ...]) -> Tuple[Ngram, ...]:
def get_4grams(words: Tuple[Word | Character | PosTag, ...]) -> Tuple[Ngram, ...]:
def chunk_NEs(doc: spacy.tokens.doc.Doc) -> Tuple[spacy.tokens.token.Token, ...]:
def get_synsets(tokens: Tuple[spacy.tokens.token.Token, ...]) -> Tuple[Word, ...]:
def remove_non_alnum(words: Tuple[Word, ...]) -> Tuple[Word, ...]:
def remove_stopwords(tokens: Tuple[spacy.tokens.token.Token, ...])
    -> Tuple[spacy.tokens.token.Token, ...]:
def get_stopwords(tokens: Tuple[spacy.tokens.token.Token, ...])
    -> Tuple[spacy.tokens.token.Token, ...]:
```

# Feature Extraction

```
lexical_functions = [
    get_characters,       # Character-level patterns
    get_tokens,           # Word tokenization
    get_token_text,       # Raw word forms
    remove_non_alnum,     # Character filtering
    get_word_pairs,       # Word co-occurrences
]

semantic_functions = [
    lemmatize_tokens,     # Normalize to base meaning
    get_synsets,          # Word meanings/concepts
    chunk_NEs,            # Named entity grouping
    get_pos_tags,         # Part of speech (bridges lexical/semantic)
]

ngram_functions = [
    get_2grams,           # Bigrams
    get_3grams,           # Trigrams
    get_4grams,           # 4-grams
]

preprocessing_functions = [
    remove_stopwords,     # Filter non-content words
    get_stopwords,        # Identify non-content words
]

all_functions = lexical_functions + semantic_functions + preprocessing_functions
```

# Feature Extraction

Cache is king { $, € }

```
@cache
def get_tokens(doc: spacy.tokens.doc.Doc) -> Tuple[spacy.tokens.token.Token, ...]:
    return tuple(token for token in doc)
```

- Many variations in ordering result in same output
- This is a prime candidate for dynamic programming
- Caching significantly speeds up feature extraction
- 520 processes x 4 metrics = 2080 features
    - across all ˜5000 sentence pairs takes ˜15 minutes

# Model Training

- Random Forest
  - Built-in feature importance analysis
  - Bagging allows discovery of local patterns
  - Handles high-dimensional feature spaces well (2080 features)
  - Resistant to overfitting
- Model Configuration
  - 100 trees in ensemble
  - No max depth, since we are interested in identifying fine-grained feature importances

# Feature Selection

- 520 permutations x 4 metrics = 2080 features
- The random forest model allows us to inspect feature importances
- We used this to identify how important the top features are to the model
- We trained and validated models with different subsets of the top features

# Model Evaluation

- Multi-level evaluation strategy
  - Initial 5-fold cross-validation on training set
  - 80/20 train/validation split for comparing feature sets
  - Held-out test set for final evaluation
- Custom Pearson correlation scorer
  - Measures linear correlation with gold standard
  - Implemented as sklearn-compatible scoring function
  - Allows direct comparison with published results

# Results

Results

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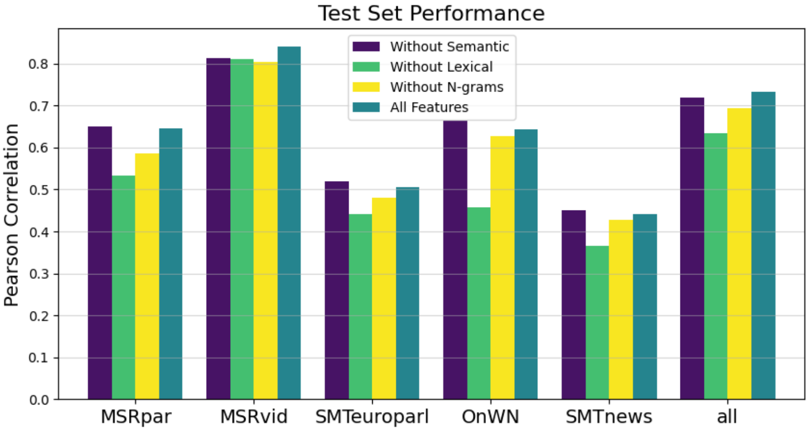
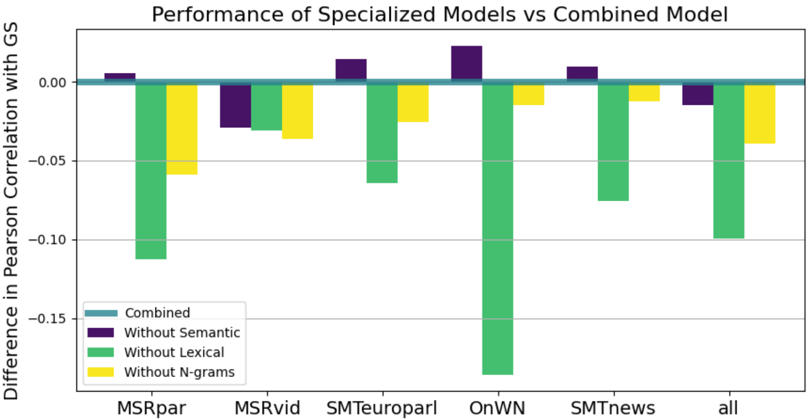

Test Set Performance
Without Semantic
Without Lexical
Without N-grams
All Features
Pearson Correlation
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
MSRpar
MSRvid
SMTeuroparl
OnWN
SMTnews
all

# Results


Performance of Specialized Models vs Combined Model
Difference in Pearson Correlation with GS
0.00
−0.05
−0.10
−0.15
Combined
Without Semantic
Without Lexical
Without N-grams
MSRpar
MSRvid
SMTeuroparl
OnWN
SMTnews
all

# Results

- **Feature Importance**
  - Top 10 features account for ˜50% of total importance
  - 60% of features (1,248) have non-zero importance
  - Reducing to 500 features shows slight performance loss
- **Feature Type Comparison**
  - Combined features perform best ($r = 0.735$ on test)
  - Lexical features alone achieve strong performance ($r = 0.718$)
  - Semantic features show lower generalization ($r = 0.640$)
  - N-grams important for generalization
- **Dataset-Specific Performance**
  - MSRvid highest performance ($r > 0.80$)
  - SMTnews and SMTeuroparl lower performance ($r < 0.52$)
  - Performance varies across datasets

# Top Features

- Jaccard similarity dominates (6 of top 10)
- Common steps: `sentence_to_doc`, `lemmatize_tokens`, `get_characters`
- N-grams frequently appear, especially 2-grams

| Feature | Processing Steps | Importance |
|---|---|---|
| score_jaccard_165 | doc → tokens → stopwords → lemma → chars → 2gram | 0.197 |
| score_cosine_257 | doc → NEs → stopwords → lemma → chars → 2gram | 0.089 |
| score_cosine_165 | doc → tokens → stopwords → lemma → chars → 2gram | 0.069 |
| score_jaccard_258 | doc → NEs → stopwords → lemma → chars → 3gram | 0.033 |
| score_cosine_258 | doc → NEs → stopwords → lemma → chars → 3gram | 0.022 |
| score_jaccard_256 | doc → NEs → stopwords → lemma → chars | 0.021 |
| score_jaccard_257 | doc → NEs → stopwords → lemma → chars → 2gram | 0.021 |
| score_cosine_166 | doc → tokens → stopwords → lemma → chars → 3gram | 0.021 |
| score_jaccard_97 | doc → NEs → lemma → chars → 2gram | 0.019 |
| score_jaccard_41 | doc → tokens → lemma → chars → 2gram | 0.019 |

# Dataset-Specific Performance

| Dataset | Without Semantic | Without Lexical | Without N-grams | All Features |
|---|---|---|---|---|
| MSRpar | 0.646 | 0.533 | 0.577 | 0.643 |
| MSRvid | 0.813 | 0.811 | 0.807 | 0.839 |
| SMTeuroparl | 0.521 | 0.437 | 0.475 | 0.495 |
| OnWN | 0.671 | 0.470 | 0.623 | 0.647 |
| SMTnews | 0.451 | 0.367 | 0.438 | 0.420 |
| All | 0.718 | 0.639 | 0.686 | 0.734 |

- Key Observations:
  - MSRvid shows consistently high performance ($r > 0.80$)
  - SMTnews and SMTeuroparl show lower performance ($r < 0.52$)
  - Performance varies significantly by dataset
  - Lexical features most important across all datasets

# Conclusions

- **Comprehensive Feature Analysis**
  - Generated and analyzed 2080 features across lexical, semantic, and n-gram types
  - Random Forests effectively identified key features
- **Key Findings**
  - Lexical features alone provide strong performance
  - N-grams enhance generalization to unseen data
  - Semantic features contribute less to generalization
- **Dataset Variability**
  - Performance varies significantly by dataset
  - MSRvid consistently high, SMTnews and SMTeuroparl lower

# Future Directions

- Explore more advanced processing steps
- Explore limitations of the approach on new domains
- Investigate feature importances on restricted feature sets (e.g. without lexical or without semantic)
- Investigate domain-specific feature engineering

# Thank You

Thank you for your attention!

Questions?

# References

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