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?
- 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

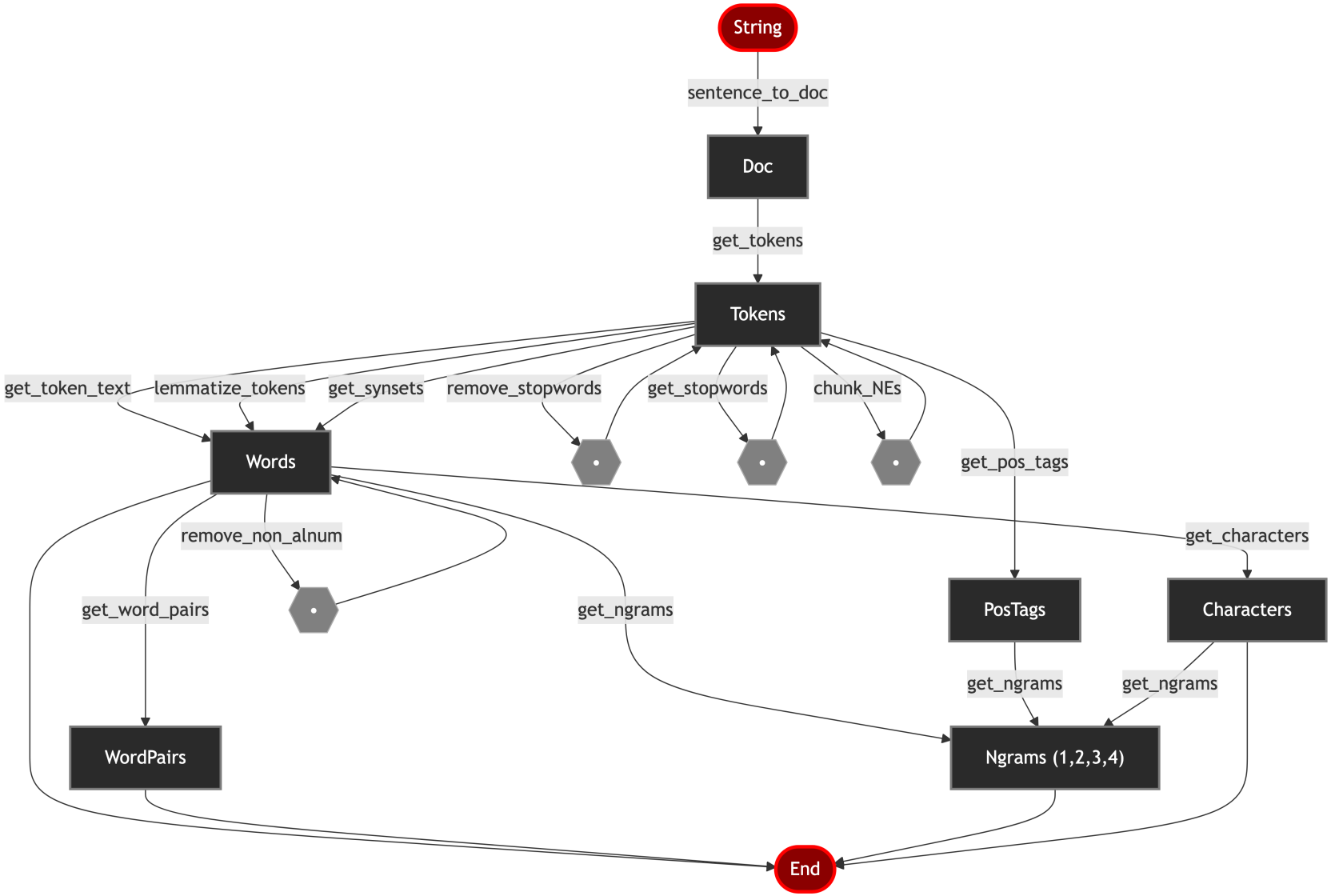
Approach

- 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

Feature Extraction

Feature Extraction

Feature Extraction



generate_valid_permutations()

```
# 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
```

```
# 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

- **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?