SemEval-2012 Task 6: Semantic Textual Similarity

A Resource-Light Supervised Approach

Introduction to Human Language Technology (IHLT)

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Task & Methodology

Objective → Predict the degree of semantic equivalence between two sentences on a continuous scale (0 to 5).

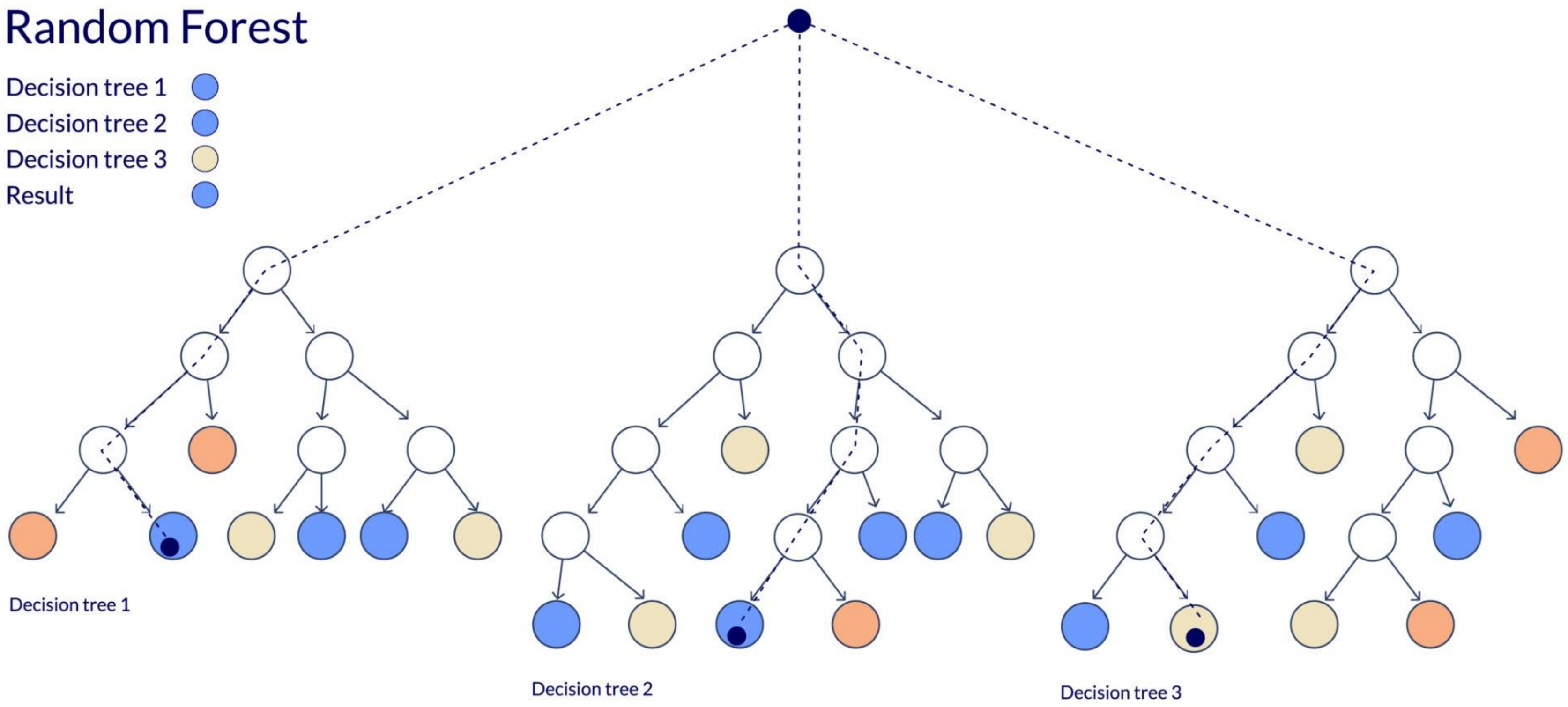
- 0: Different topics.
- 5: Completely equivalent.

Constraint: "Resource-Light." We avoided pre-trained Deep Learning embeddings (BERT/GloVe) to focus on interpretable linguistic features.

Approach: Supervised Machine Learning (Random Forest) with iterative feature engineering.

Inspiration: Built on top SemEval-2012 systems:

- **UKP Lab (Rank 1):** String similarity & log-linear models.
- **TakeLab (Rank 2):** Syntactic dependencies & SVR.


Random Forest
Decision tree 1
Decision tree 2
Decision tree 3
Result
Decision tree 1
Decision tree 2
Decision tree 3

Feature Engineering

Core Layers:

- **Lexical (Surface):** Jaccard Similarity, Overlap Coefficient, Length Difference. Based on UKP Lab's n-gram approach.
- **Semantic (Meaning):** WordNet Path Similarity. Captures synonyms (e.g., "car" $\approx$ "automobile"). Based on TakeLab.

Syntactic (Structure): spaCy Dependency Parsing. Checks if Subject, Object, and Root Verb align. **Domain Boosters:**

- **Negation:** Critical for News ("did" vs "did not").
- **Numbers:** Quantifies digit overlap ("$5" vs "$50"). ***MT Metrics:** BLEU & LCS (suited for Machine Translation datasets).

Phase 1 – The Baseline

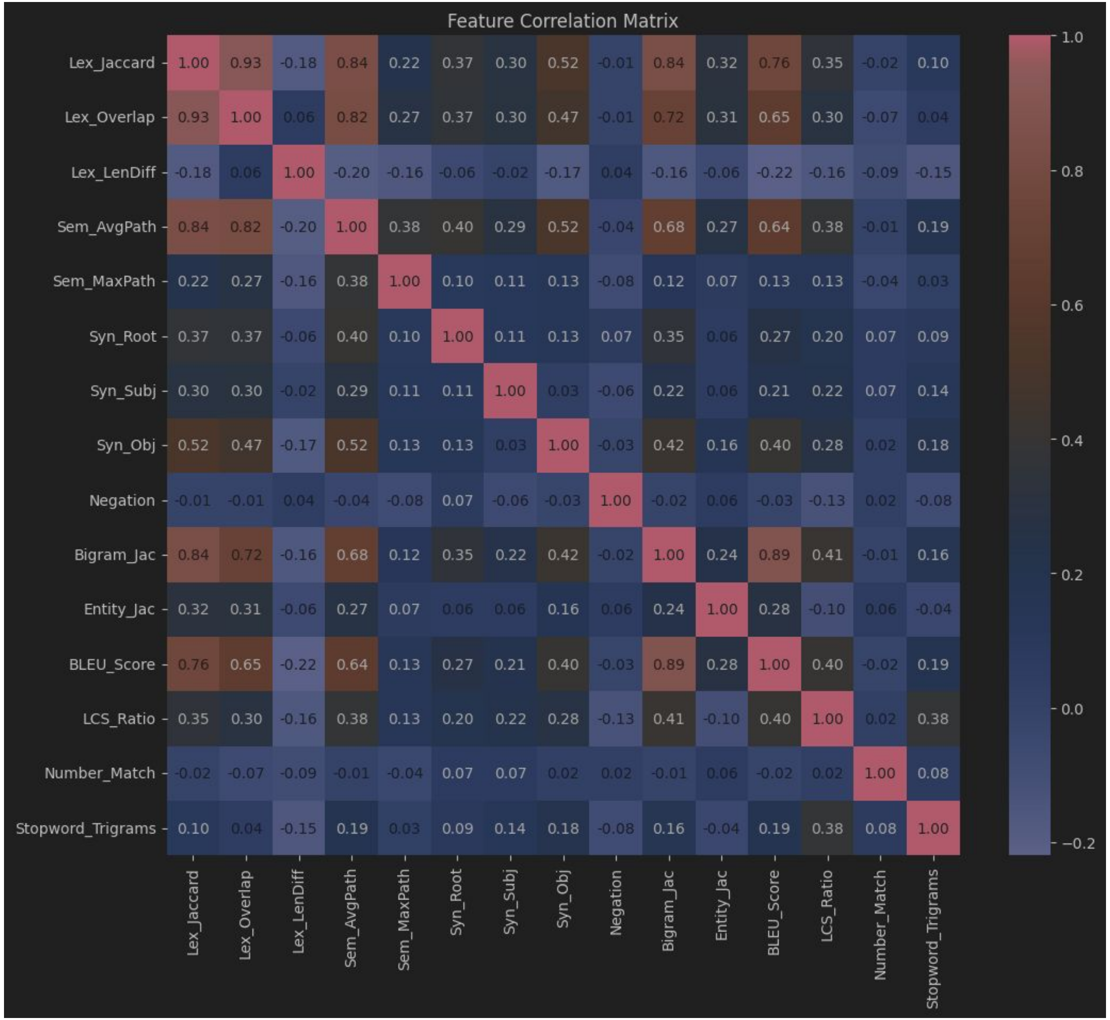
Hypothesis: Simple lexical overlap + WordNet synonyms should capture basic similarity.

Initial Features:

- Lexical: Jaccard Similarity, Overlap Coefficient.
- Semantic: WordNet Path Similarity (capturing "car" ≈ "automobile").

Initial Results:

- 🟢 MSRvid: 0.763 (Success: Works well on simple descriptions).
- 🔴 MSRpar: 0.402 (Failure: Cannot distinguish complex news headlines).


Feature Correlation Matrix
Lex_Jaccard
Lex_Overlap
Lex_LenDiff
Sem_AvgPath
Sem_MaxPath
Syn_Root
Syn_Subj
Syn_Obj
Negation
Bigram_Jac
Entity_Jac
BLEU_Score
LCS_Ratio
Number_Match
Stopword_Trigrams
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

Phase 2 – Context & Debugging

Diagnosis: The low MSRpar score suggested the model missed "logical" differences or context.

- *Example:* "The bird is flying" vs "The bird is not flying."

Features Added:

- **Negation Detection:** Explicit check for "not", "no", "never", "n't".
- **Named Entities:** Matching people, organizations, and locations via spaCy.

Result → 🟢 MSRpar improved to 0.512 (+0.11 gain)

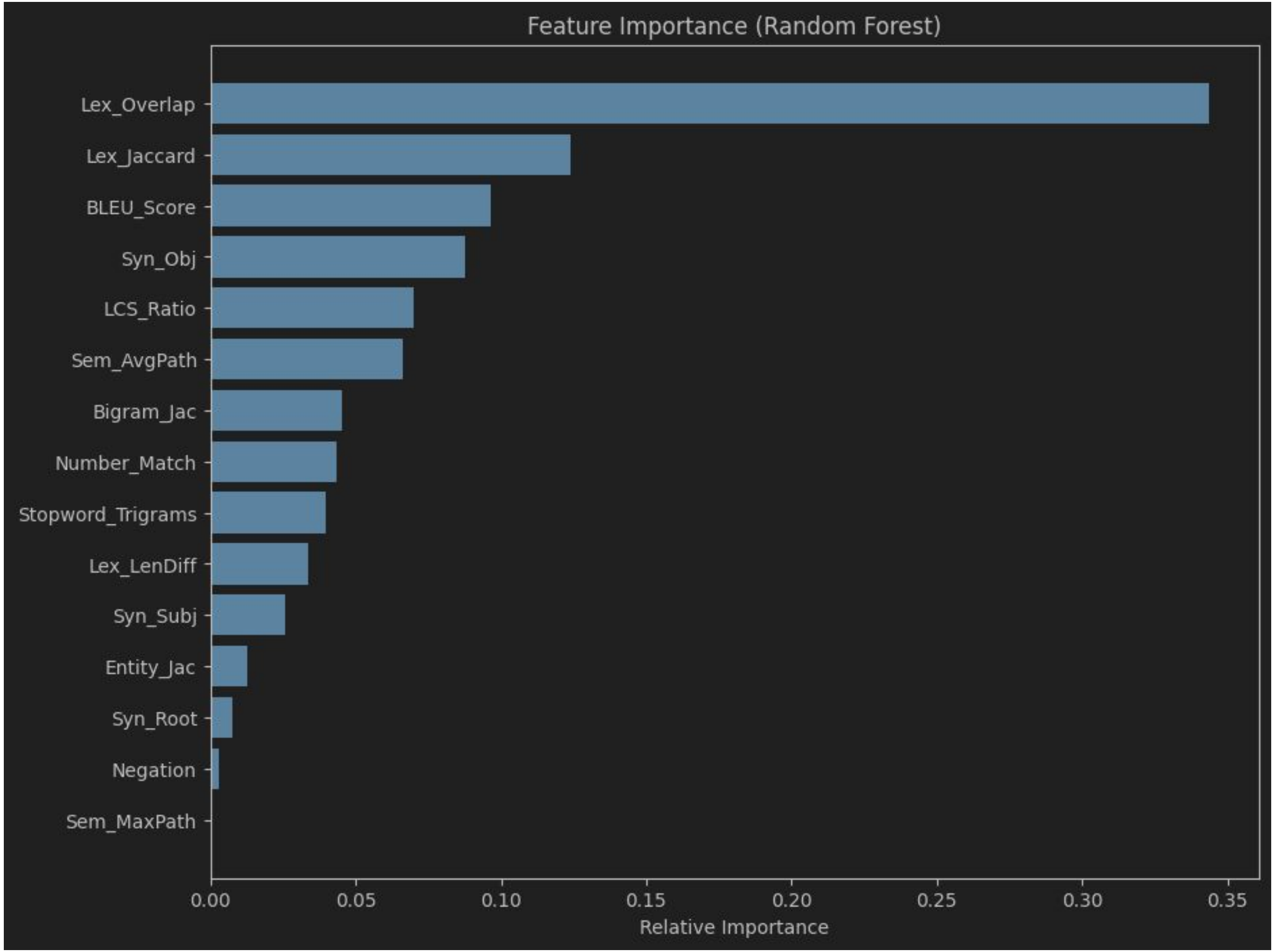
Phase 3 – Domain Adaptation

The News Problem: News datasets rely heavily on specific dates, money, and quantities. Standard similarity metrics ignore these "details."

Domain Boosters:

- **Number Matching:** Quantifies overlap of digits/years ("$5" vs "$50").
- **BLEU Score:** Standard metric for Machine Translation evaluation.
- **LCS Ratio:** Longest Common Subsequence to check word order.

Result → 🟢 MSRpar exploded to 0.661. Number matching was the key differentiator.



Feature Importance (Random Forest)
Lex_Overlap
Lex_Jaccard
BLEU_Score
Syn_Obj
LCS_Ratio
Sem_AvgPath
Bigram_Jac
Number_Match
Stopword_Trigrams
Lex_LenDiff
Syn_Subj
Entity_Jac
Syn_Root
Negation
Sem_MaxPath
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Relative Importance

Phase 4 – Stylistic Refinement

The SMT Problem: Syntactic parsers punish "garbled" output from Machine Translation datasets (SMTeuroparl/SMTnews), lowering scores.

The Fix:

- **Stopword n-Grams:** Captures structural/stylistic similarity (e.g., "of the...", "in the...") without demanding perfect grammar.

Final System:

- **Total Features:** 15 Dimensions.
- **Model:** Random Forest (Handles boolean and float features robustly).

Analysis – Model & Feature Selection

Ablation Study (Validation): We compared models on isolated feature sets (Lexical-Only vs. Syntactic-Only).

- **Result:** The Combined Ensemble outperformed the individual baselines by ~0.10 Pearson *r*.
- **Conclusion:** This suggests that syntax acts as a multiplier for lexical features rather than a replacement.

Parsimony Check: We tested retraining the model on subsets of features (Top-5 vs. All-15).

- **Top-5 Features:** $r = 0.767$
- **All 15 Features:** $r = 0.833$
- **Finding:** Pruning features caused a notable drop in accuracy. We retained the full 15-feature set for the final system.

Cell 3 Output: Validation Leaderboard Table

	Model	Val_P…
7	SVR-Comb	0.832124
8	RF-Comb	0.832080
6	Ridge-C…	0.728750
2	RF-Lex	0.728720
1	SVR-Lex	0.708024
5	RF-Syn	0.699326
4	SVR-Syn	0.675709
0	Ridge-L…	0.606667
3	Ridge-S…	0.492885

Cell 5 Output: Feature Selection Table

```
--- Feature Selection Experiment (Top-K) ---
             Subset  Val_Pearson
0    Top-3 Features     0.755725
1    Top-5 Features     0.767350
2   Top-10 Features     0.822444
3   Top-15 Features     0.832766

Best Subset: Top-15 Features (r=0.8328)
```

Final Evaluation (Test Set)

Summary:

- **Final Macro-Average Pearson:** 0.608 (Substantially higher than the official SemEval baseline of 0.311)

Dataset	Pearson (*r*)	Performance
MSRvid	0.833	🟢 Excellent (Simple descriptions)
OnWN	0.663	🟡 Good (Definitions)
MSRpar	0.661	🟡 Good (News Paraphrases)
SMTnews	0.433	🔴 Fair (Noisy Input)
SMTeuroparl	0.448	🔴 Fair (Noisy Input)

Cell 7 Output: *evaluate.sh* Evaluation

```
==========================================
       RUNNING SEMEVAL EVALUATION
==========================================
Dataset: MSRpar ... Pearson: 0.66083
Dataset: MSRvid ... Pearson: 0.83347
Dataset: SMTeuroparl ... Pearson: 0.44814
Dataset: OnWN ... Pearson: 0.66336
Dataset: SMTnews ... Pearson: 0.43389
==========================================
Final Macro-Average Pearson: 0.60794
==========================================
```

Comparison with State-of-the-Art – Complexity vs. Efficiency

UKP Lab (Rank 1): Utilized massive external knowledge bases (Wikipedia, Wiktionary) and 300+ features (mostly n-grams).

TakeLab (Rank 2): Heavily relied on "Distributional Semantics" (LSA) trained on large corpora (NYT/Wikipedia) and syntactic dependencies.

- **Our Approach: "Resource-Light."** We used 0 external corpora and only 15 features.
- **Conclusion:** We achieved comparable performance on MSRvid with <5% of computational complexity.

System	Macro-Avg (All)	MSRpar	MSRvid	OnWN	SMTnews
UKP Lab (Rank 1)	**0.823**	0.724	0.868	0.679*	0.398*
TakeLab (Rank 2)	0.813	**0.734**	**0.880**	0.679	0.400
Official Baseline	0.311	0.433	0.299	0.586	0.390
Our System	**0.608**	**0.661**	**0.833**	**0.663**	**0.433**

Conclusion & Future Work

Success: Achieved >0.8 correlation on validation/video data using only classical NLP (no Neural Networks).

Key Insight: No "one-size-fits-all" feature exists. The Ensemble allows the model to switch strategies (e.g., using **Negation** for News vs. **Jaccard** for Videos).

Future Work:

- **Distributional Semantics:** Incorporate LSA/LDA to handle idioms where word overlap is zero.
- **Knowledge Graphs:** Better entity linking for proper nouns.

References

[1] D. Bär, C. Biemann, I. Gurevych, and T. Zesch, "UKP: Computing Semantic Textual Similarity by Combining Multiple Content Similarity Measures," in *Proceedings of the First Joint Conference on Lexical and Computational Semantics (SEM 2012), Montréal, Canada, 2012, pp. 435–440.

[2] F. Šarić, G. Glavaš, M. Karan, J. Šnajder, and B. Dalbelo Bašić, "TakeLab: Systems for Measuring Semantic Text Similarity," in *Proceedings of the First Joint Conference on Lexical and Computational Semantics (SEM 2012), Montréal, Canada, 2012, pp. 441–448.