# A Joint Syntactic-Semantic Representation for Recognizing Textual *Relatedness*

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# RTE from 2-Way to 3-Way

- From RTE-3 pilot task
  - YES → Entailment
  - NO → Contradiction / Unknown

- Performance
  - RTE-4 (3-way): 0.51
  - RTE-4 (2-way): 0.57
  - RTE-3 (2-Way): 0.61

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# An Example

- Text: *At least five people have been killed in a head-on train collision in north-eastern France, while others are still trapped in the wreckage. All the victims are adults.*

- Hypothesis: *A French train crash killed children.*

# An Example

- Text: *At least five people have been killed in a head-on train collision in north-eastern France, while others are still trapped in the wreckage. All the victims are adults.*

- Hypothesis: *A French train crash killed children.*

- *Contradictory but Related!*

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# Entailment vs. Relatedness

- Textual Entailment
  - Unidirectional
  - Meaning preserved
  - Entailment vs. Non-entailment

- Textual Relatedness
  - Bidirectional
  - Weaker than similarity and stronger than co-occurrence
  - Related vs. Non-related (Unknown)

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# Strategies for 3-Way RTE

- Traditional 2-way classification
  - Split E cases first: ECU → E/CU
- Contradiction recognition (de Marneffe et al., 2008)
  - Split C cases first: ECU → C/EU
- Others
  - Three-way classification: ECU → E/C/U
  - Split U cases first: ECU → U/EC

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# Baseline

- RTE-4 dataset
  - 500 E, 150 C, 350 U
  - NaiveBayes classifier, 10-fold CV
  - BoW + SynDep features (Wang and Neumann, 2007)

| Three-Way | Two-Stage | | |
|---|---|---|---|
| $E/C/U$ | $E/CU \rightarrow E/C/U$ | $C/EU \rightarrow C/E/U$ | $U/EC \rightarrow U/E/C$ |
| 53.20% | 50.00% | 53.50% | 54.20% |
| / | 82.80% | 68.70% | 84.90% |

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# Outline

- Recognizing Textual Relatedness
  - Related Work
  - Definition
- The Joint Representation
  - Syntactic and Semantic dependency
  - Co-reference
- Experiments & Results
- Conclusion & Future Work

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# RTE vs. RTR

- RTE
  - Direct three-way classification (e.g. Agichtein et al., 2009); different rules simultaneously (Clark and Harrison, 2009)
  - Contradiction recognition (de Marneffe et al., 2008)

- Alignment
  - Phrased-based and dependency-graph-based (Pado et al., 2009)
  - Ontology-based (Siblini and Kosseim, 2009)
  - Dependency-path-based (Wang and Neumann, 2007)

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# Textual Relatedness

- Wang and Zhang (2009)
  - *If **H** is fully relevant to part of **T**, **H** is semantically related to **T**.*
- Relatedness
  - (Weaker than) Similarity
    - Surface string, semantic, etc.
  - (Stronger than) Co-occurrence
    - Distributionally or ontologically

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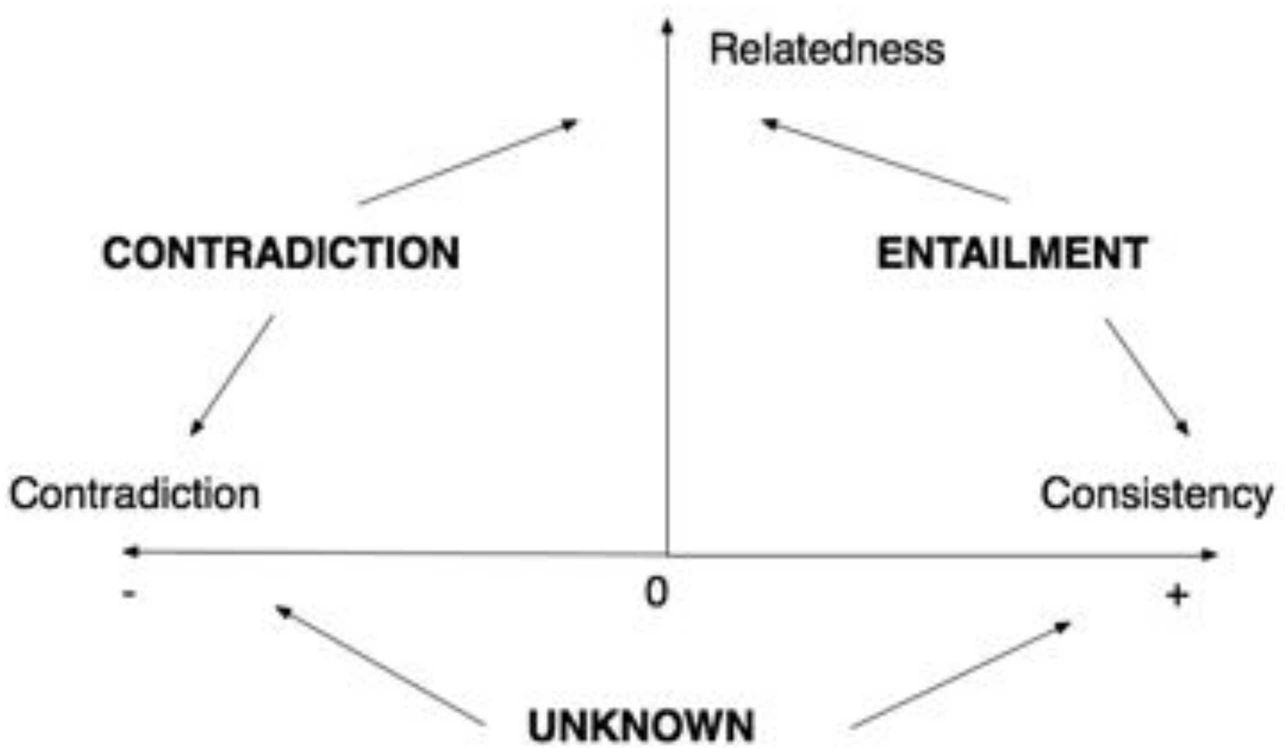
# Relationship between Relations

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# Recognizing Textual Relatedness

- Preprocessing
- Dependency Parsing (MSTParser – McDonald et al. (2005))
- Semantic Role Labeling (Zhang et al., 2008)
  - The CoNLL shared task (2008, 2009): 70~80%
- Co-reference Resolution (BART – Versley et al. (2008))

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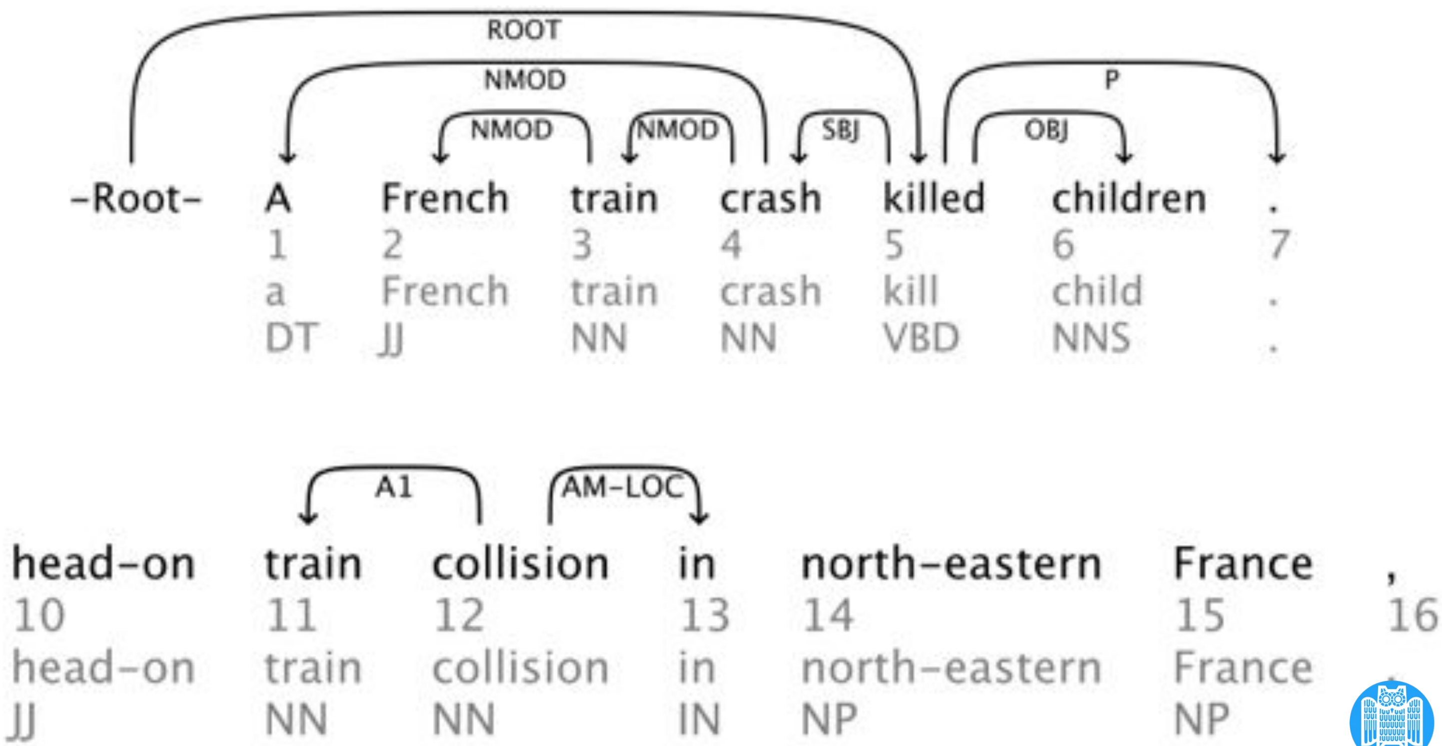
# Syntactic and Semantic Dependency

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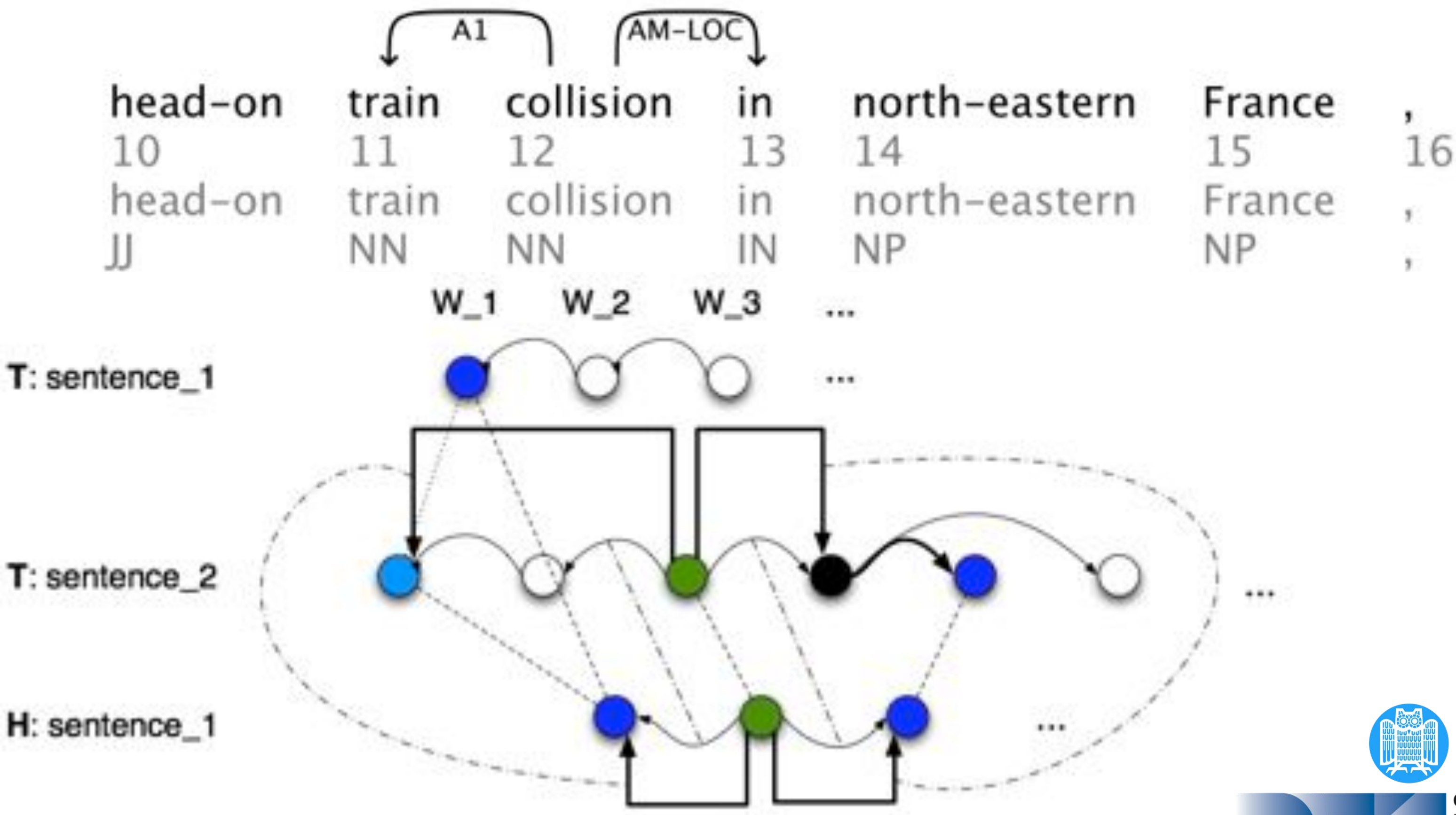
# The Joint Representation

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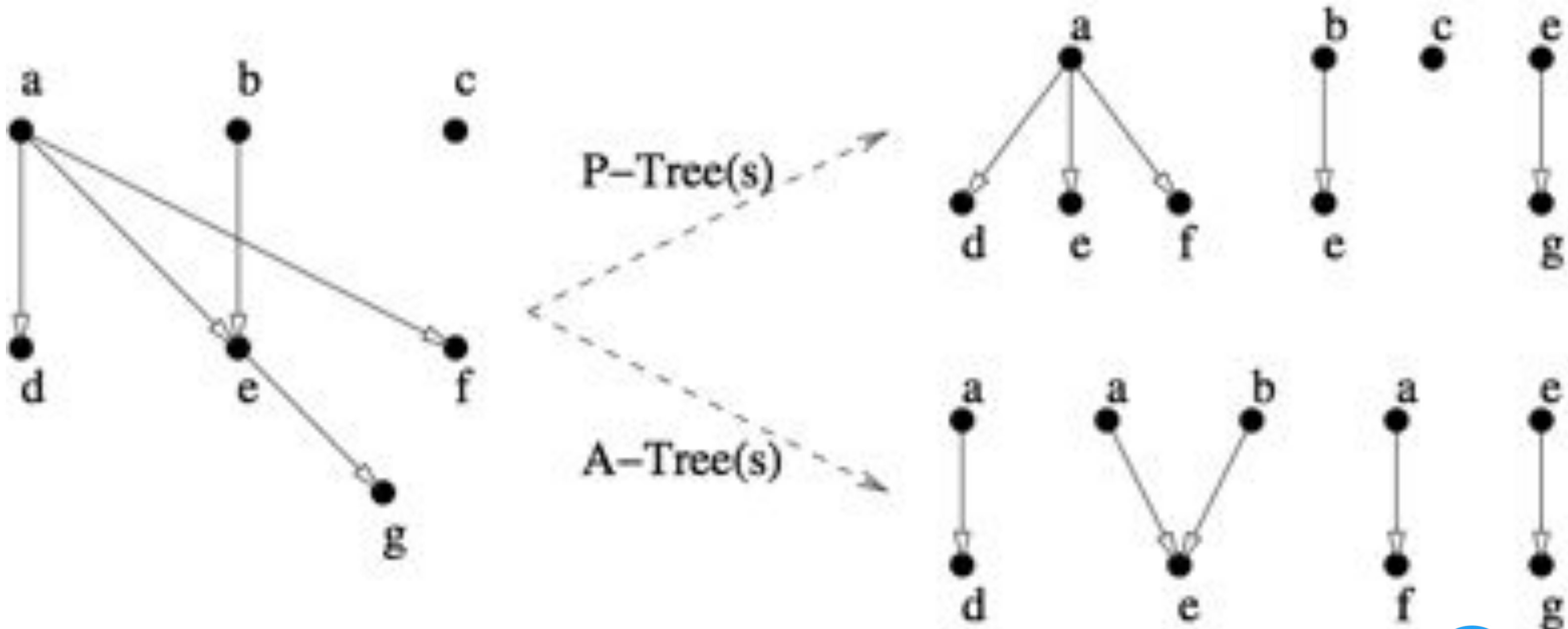
# Decomposition of the Joint Graph

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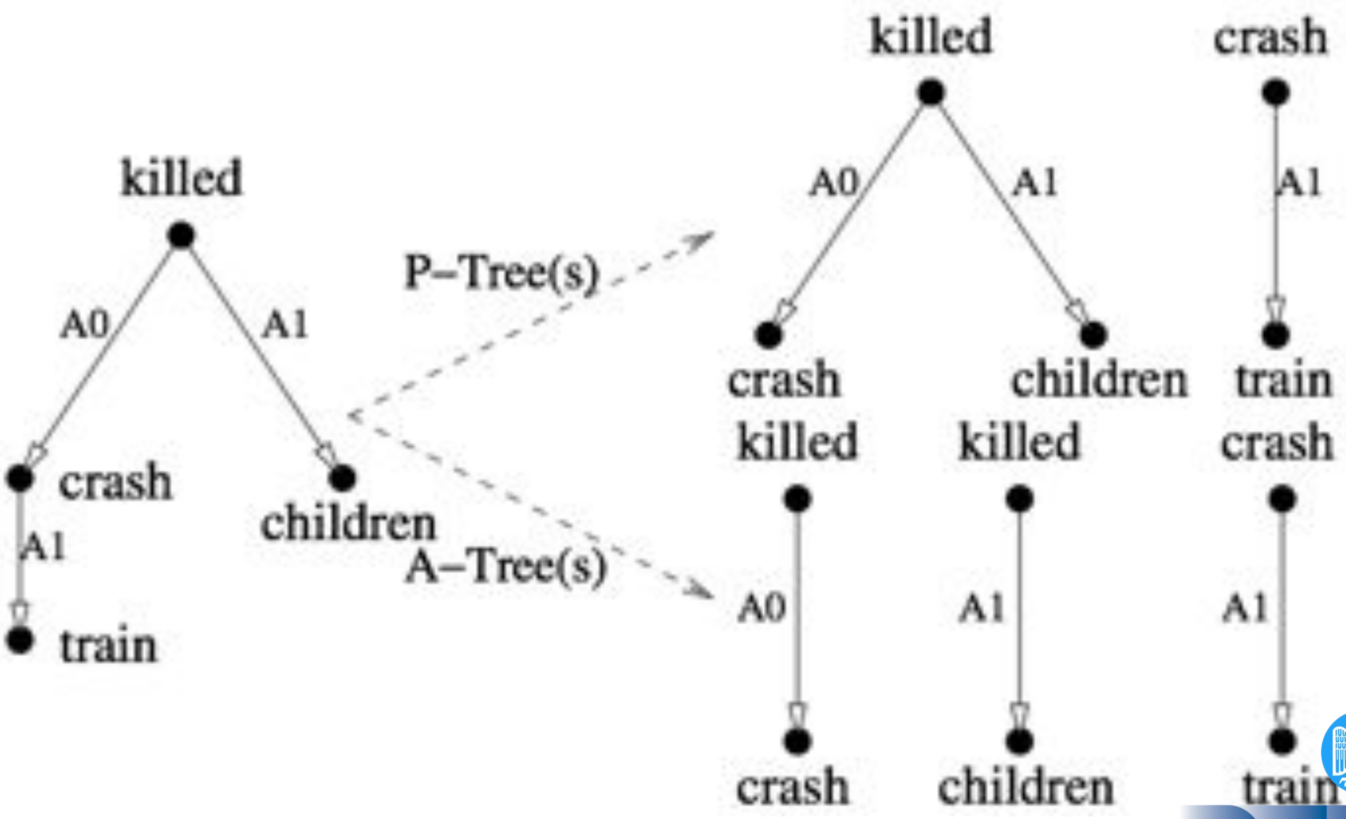
# Decomposition (cont.)



# Equations

$$R(T,H) = \max_{1 \le i \le r, 1 \le j \le s} \{R(Tree_{T_i}, Tree_{H_j})\}$$

$$R(Tree_T, Tree_H) = \min_{1 \le i \le n, 1 \le j \le m} \{R(\langle P_T, D_{T_i}, A_{T_i} \rangle, \langle P_H, D_{H_j}, A_{H_j} \rangle)\}$$

$$R(\langle P_T, D_T, A_T \rangle, \langle P_H, D_H, A_H \rangle) = \begin{cases} \text{Full} & R(P_T,P_H)=R(D_T,D_H)=R(A_T,A_H)=1 \\ \text{NotFull} & R(P_T,P_H)=R(D_T,D_H)=1 \\ \text{Other} & \text{Otherwise} \end{cases}$$

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# Lexical Semantic Resources

- String matching of lemmas
- Predicate
  - VerbOcean (Chklovski and Pantel, 2004)
  - Normalized Google Distance (NGD) (Cilibrasi and Vitanyi, 2007)
- Argument
  - WordNet: synonym, hypernym, hyponym, antonym
  - NGD (available online)

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# Experiments

- Run1
  - Wang and Zhang's system + a backup using features from BoW and syntactic dependency
- Run2
  - The main system (lenient) + a backup using features from BoW, syntactic, and semantic dependency
- Run3
  - The main system (strict) + a backup using features from BoW and joint representation

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# Results

| Runs | Main | Main -VO | Main -WN | Main -VO-WN |
|---|---|---|---|---|
| DFKI1 | 50.7% | 50.5% | 50.7% | 50.5% |
| DFKI2 | 63.7% | 63.2% | 63.3% | 63.0% |
| DFKI3 | 63.5% | 63.3% | 63.3% | 63.3% |
| | | | | |
| RTE-3 | 53.69% | 53.19% | 53.50% | 52.88% |
| RTE-4 | 56.60% | 56.00% | 56.10% | 55.7[illegible] |

# Results (cont.)

| DFKI2 | | Gold-Standard | | | |
|---|---|---|---|---|---|
| | | E | C | U | Total |
| System | E | 238 | 60 | 77 | 375 |
| | C | 4 | 21 | 10 | 35 |
| | U | 58 | 9 | 123 | 190 |
| | Total | 300 | 90 | 210 | 600 |

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# Results (cont.)

| Runs | Main | Main -VO | Main -WN | Main -VO-WN |
|---|---|---|---|---|
| DFKI1 | 62.5% | 62.5% | 62.7% | 62.5% |
| DFKI2 | 66.8% | 66.5% | 66.7% | 66.3% |
| DFKI3 | **68.5%** | 68.3% | 68.3% | 68.3% |

| Runs | Main | Main -VO | Main -WN | Main -VO-WN |
|---|---|---|---|---|
| DFKI1 | 74.0% | 73.7% | 73.8% | 73.7% |
| DFKI2 | **74.3%** | 73.7% | 73.8% | 73.5% |
| DFKI3 | 72.3% | 72.2% | 72.2% | 72.2% |

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# Summary

- Strategy
  - 2-stage binary classification for 3-way RTE
- Approach
  - Textual relatedness
  - Use a joint representation measure it
- Result
  - Improved (combination)
  - Lexical resources

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# Future Work

- Two styles of alignment
  - Predicate (Dinu and Wang, 2009)
  - Argument (paraphrase resources?)
- Entailment vs. Contradiction
  - Fine-grained RTE
  - Specialized RTE modules
- Named-Entity vs. common nouns

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# Thank you!

- Questions?
- Or later →→→