



Variants of Vector Space Reductions for Predicting the Compositionality of English Noun Compounds

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Observation

The relationship between noun compounds and their constituents' meanings is not always the same.

- Snow-ball: A **ball** made of **snow**
- Butter-fly: Something that **flies**; Not clearly related to butter

It's crucial for NLP applications that we know the interaction between compounds and constituents' properties.

Literature

There's been research on automatic prediction of the **degree of compositionality** of compounds.

Automatic prediction uses properties of compounds and constituents and/or the compounds' similarity to their constituents.

Degree of Compositionality: A measure of relatedness between a compound's meaning and its constituents' meanings

Measure of Similarity: Usually words are represented with vectors in a vector space and their similarity is calculated as a function of vectors.

Our Contribution

We evaluated the role of vector-space reductions on the prediction of the compositionality degree of English noun compounds.

Zooming on Compounds and Constituents' Properties

- We split the words into categories based on their value of:
 - Compound frequency
 - Head productivity
 - Modifier productivity
 - Compound compositionality
 - Head compositionality
 - Modifier compositionality
- We then evaluated the predictions on each subset

Setting

Datasets:

- Text data for making word vectors: ENCOW16 (Schäfer and Bildhauer (2012))
 - English COpora from the Web
- Gold standard data for compounds' compositionality degree:
 - Provided by Reddy, et al (2011)
 - A list of English noun compounds and their constituents
 - Human judgement on the compositionality degree of the compounds and also properties of constituents

Training word vectors

- All trained with a window size of 10

POS parser

- The TreeTagger by Schmid, 1994 is used for POS tagging and lemmatization

Measure

- We used **cosine** as a measure of similarity between word vectors.
- We used the Spearman Rank-Order Correlation Coefficient (Siegel and Castellan, 1988) to compare the predicted results with human judgement.

Vector Space Variations

- **ALL** : All context words
- **POS Matrices**
 - **VV**: All context verbs
 - **NN**: All context nouns
 - **NN-k**: k most frequent corpus nouns
- **PCA reductions**
 - **ALL-PCA-k**: PCA with k dimensions on ALL
 - **NN-PCA-k**: PCA with k dimensions on NN
- **Word2vec**: 300d Word2vec vectors

Prediction Functions

- **WORD1**: Use only the compound-modifier cosine score
- **WORD2**: Use only the compound-head cosine score
- **ADD**: Add the compound-modifier and compound-head cosine scores
- **MULT**: Multiply the compound-modifier and compound-head cosine scores
- **COMB**: Add the compound-modifier, compound-head and the multiplication of both cosine scores

Main Results

- **Word2vec** performs generally better than the other vector-space variants.
- The nouns matrix outperforms the verbs matrix and the whole matrix.
- Performing **PCA reduction doesn't improve** the results.
- Reducing the nouns matrix to the k most frequent nouns leads to better results for some values of k. It gets better with increasing k, but reaches to a maximum around k=25000-30000.

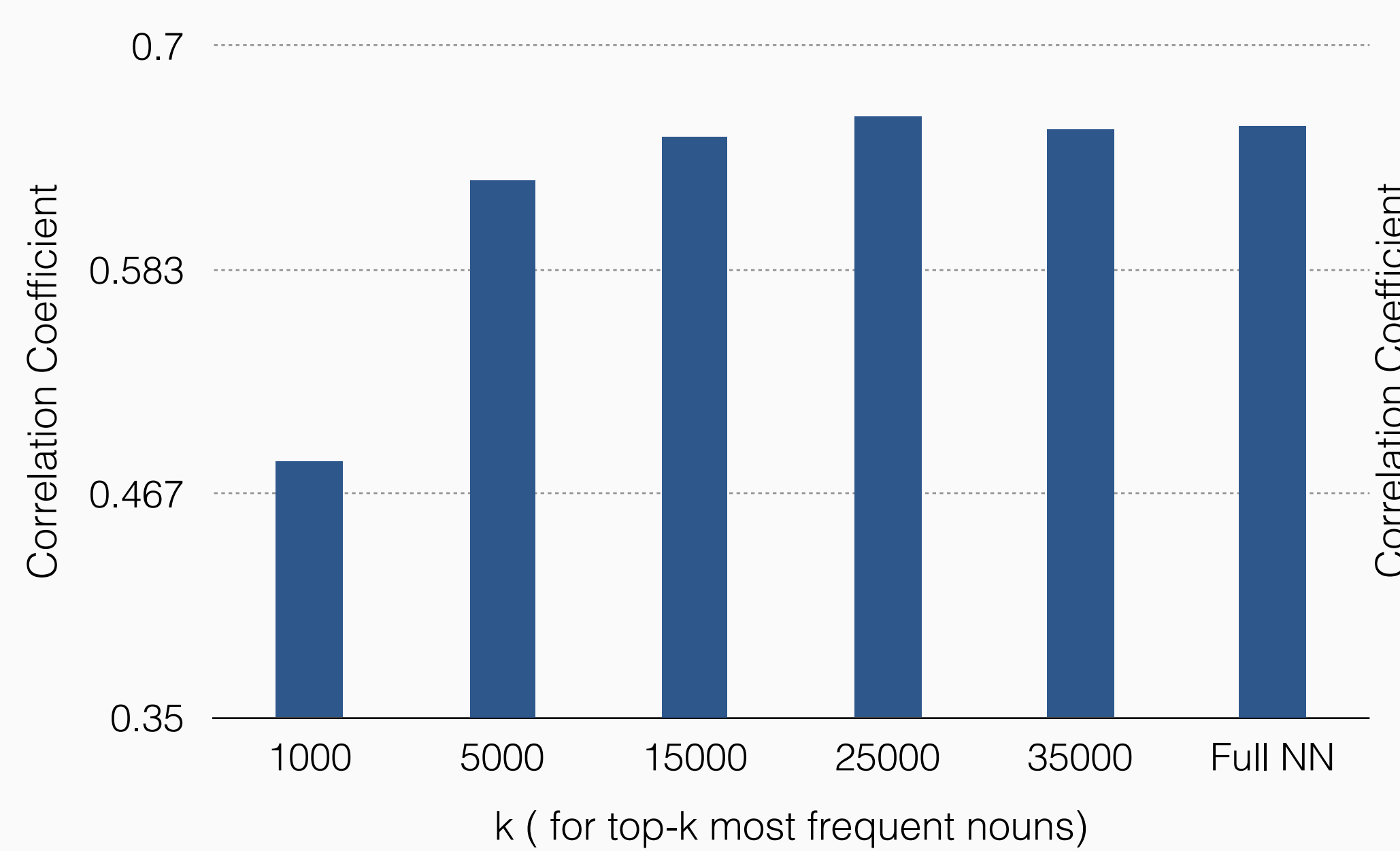
Properties' Results

- All variants but Word2vec perform **better on mid-frequent compounds** and the prediction on that subset is better than on average.
- Modifier productivity doesn't seem to affect prediction results, but the results are **better for compounds with mid-productive heads**.
- Results are significantly **better for compounds with high-compositional heads**.

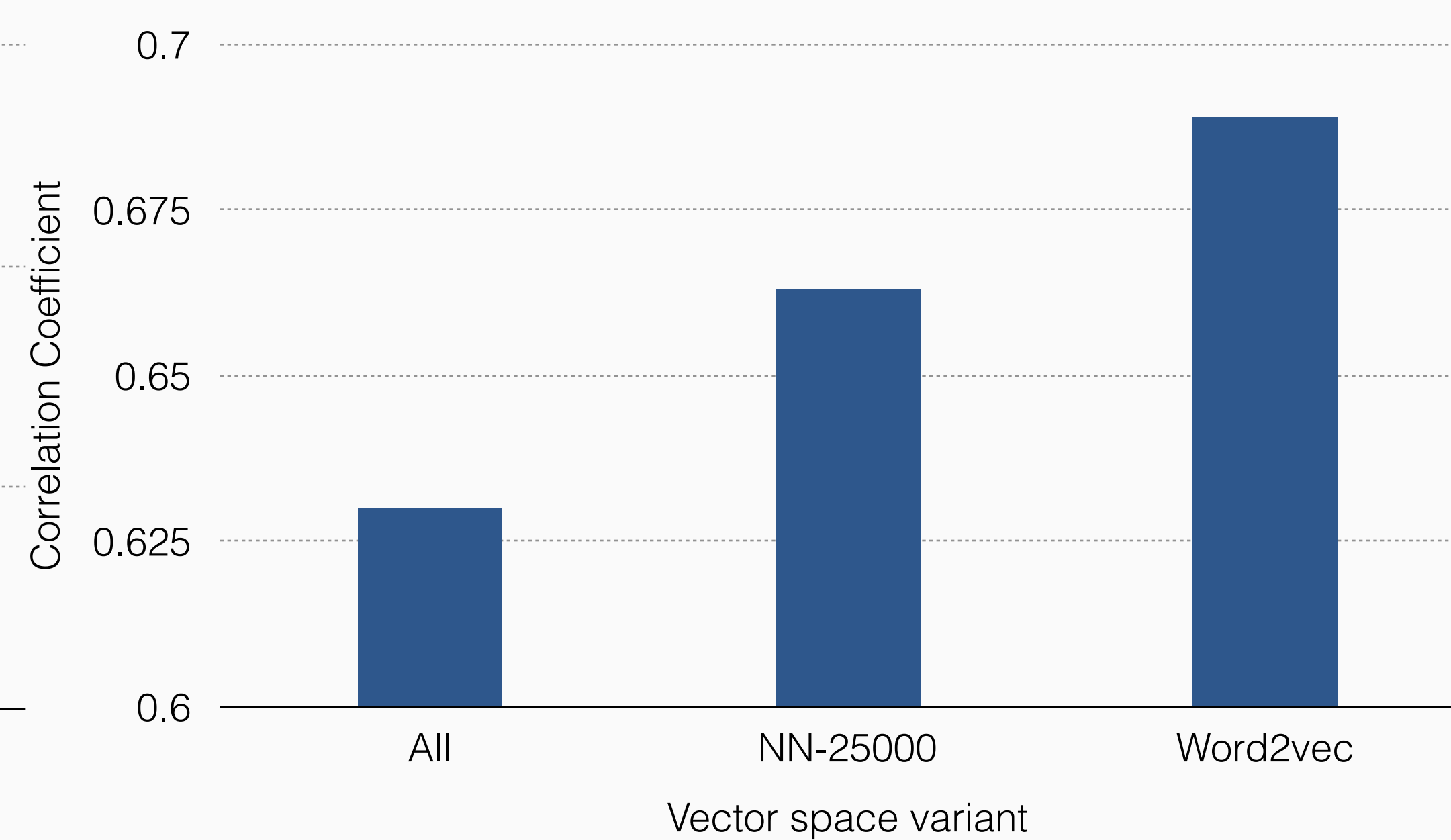
Conclusion

- **Word2vec with 300 dimensions is the winner**, both in best performance and stability over different prediction functions.
- The second best results were obtained when using a **large subset of context nouns**.
- While ADD, MULT and COMB are better prediction functions overall, while zooming on subsets of words using just head-compound or modifier-compound similarity can be enough.

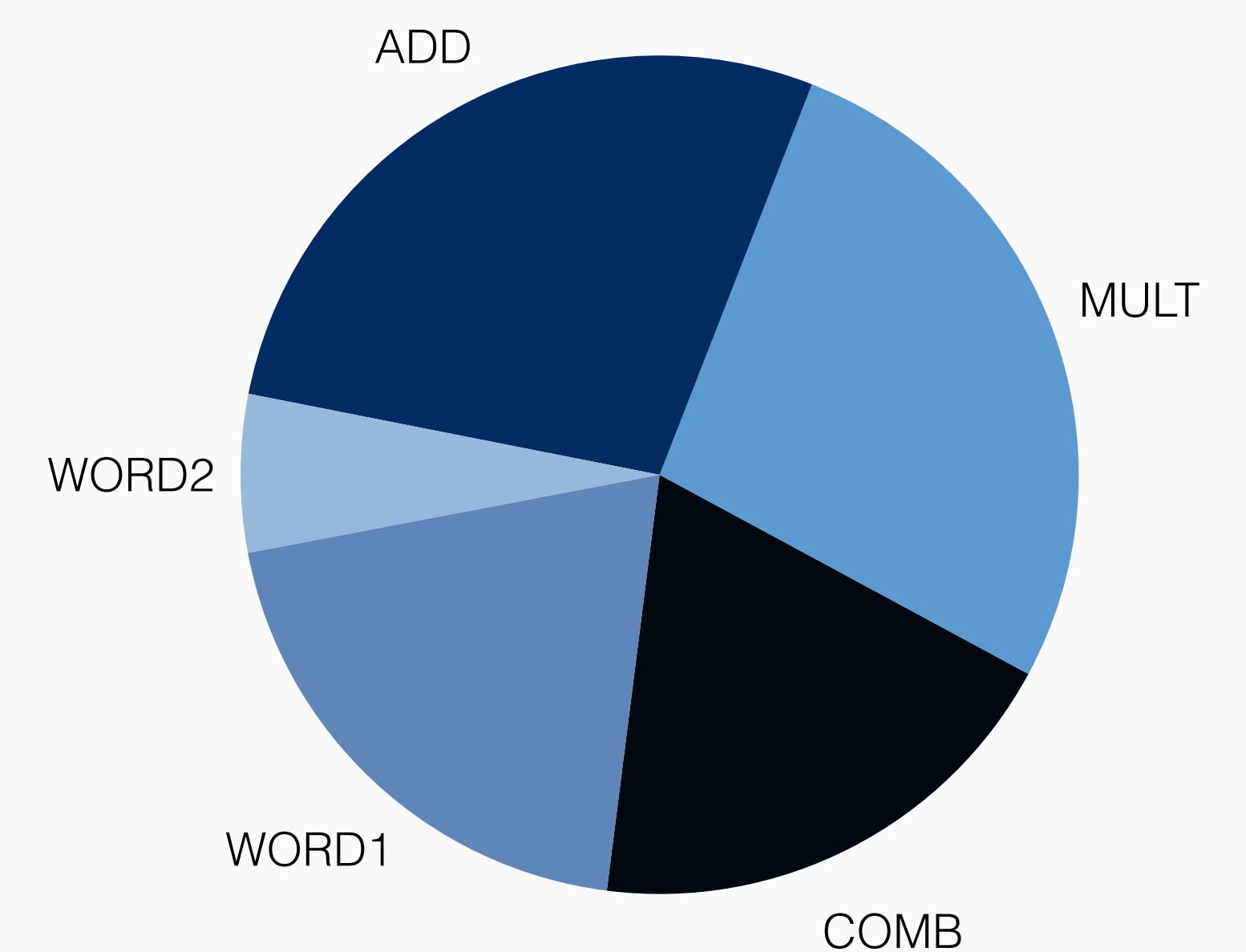
Comparison between best results of **NN-k** vectors



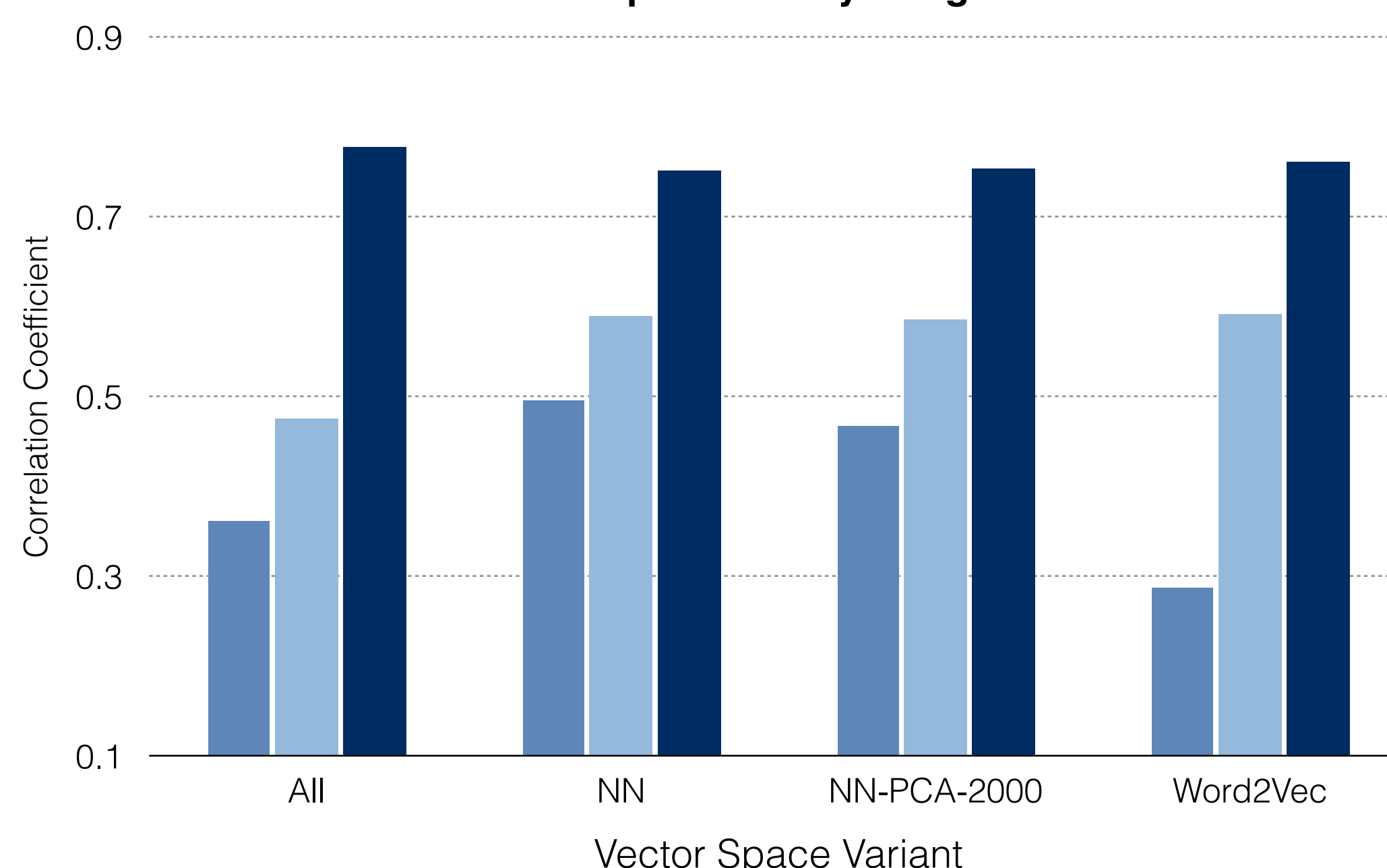
Comparison between NN best results among each group



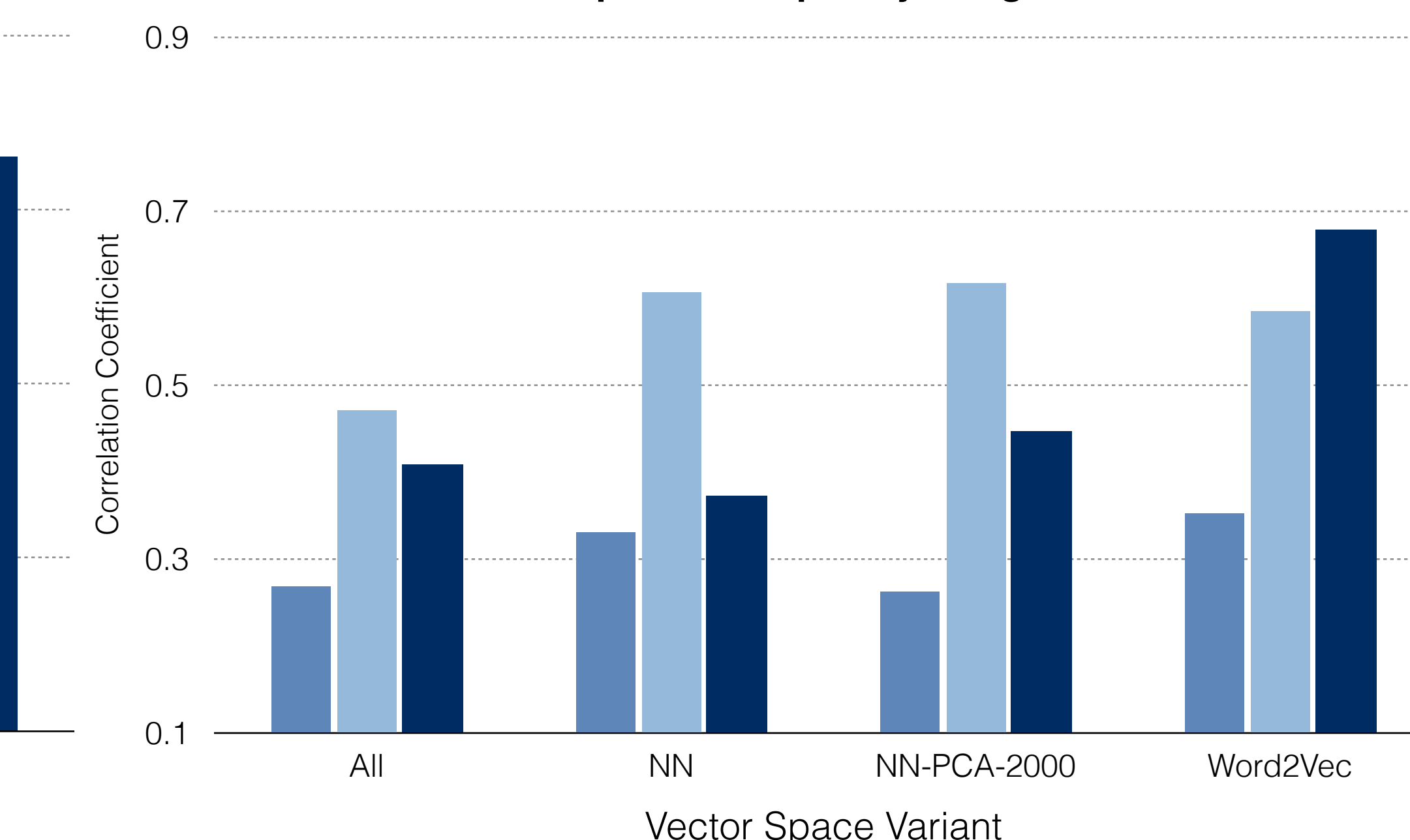
Number of Experiments that Each **Prediction Function** Provided the Best Result of All



Best Performance of Vector Space Variants Across **Head Compositionality Range**



Best Performance of Vector Space Variants Across **Compound Frequency Range**



Best Performance of Vector Space Variants Across **Modifier Compositionality Range**

