Final

April 14, 2025

0.1 Libraries

[2]:
```
import gensim
import pandas as pd
import spacy
import numpy as np
from wefe.word_embedding_model import WordEmbeddingModel
from scipy.stats import pearsonr
from wefe.metrics import RIPA
from wefe.query import Query
import re
from gensim.models import KeyedVectors
import logging
import matplotlib.pyplot as plt
import seaborn as sns
import random
```

[3]:
```
# Configure logging
logging.basicConfig(
    level=logging.INFO,
    format='%(asctime)s [%(levelname)s] %(message)s'
)
```

0.2 Helper Functions

[4]:
```
def cosine_similarity(v1: np.ndarray, v2: np.ndarray) -> float:
    return np.dot(v1, v2) / (np.linalg.norm(v1) * np.linalg.norm(v2))

def compute_bias(adj, male_terms, female_terms, model):
    male_mean = np.mean([cosine_similarity(model[adj], model[m]) for m in␣
 ↪male_terms if m in model])
    female_mean = np.mean([cosine_similarity(model[adj], model[f]) for f in␣
 ↪female_terms if f in model])
    return male_mean - female_mean

def compute_individual_bias(
    adjectives,
    male_terms,
```

```
    female_terms,
    model,
    exclude_substrings=True
):
    """
    Computes, for each adjective, the 'bias' difference between the average
    cosine similarity with male terms and the average cosine similarity
    with female terms.

    Parameters
    ----------
    adjectives : list of str
        List of adjectives to be analyzed (already cleaned/lemmatized).
    male_terms : list of str
        Words representing 'masculinity' (e.g., ['man', 'boy', 'father', ...]).
    female_terms : list of str
        Words representing 'femininity' (e.g., ['woman', 'girl', 'lady', ...]).
    model : dict-like of {str -> np.ndarray} or a KeyedVectors-like object
        Your embedding model, where you can check `word in model` and
        retrieve vectors using `model[word]`.
    exclude_substrings : bool, default=True
        Whether to exclude adjectives that contain any of the male or female
        terms as substrings (e.g., "manlike" contains "man").

    Returns
    -------
    pd.DataFrame
        DataFrame with columns:
        ['word', 'male_mean', 'female_mean', 'bias_value'].
        Where 'bias_value' = male_mean - female_mean.
        Rows without sufficient embedding data are skipped.
    """

    # 1) filter out adjectives containing gender terms as substrings
    if exclude_substrings:
        all_target_words = set(male_terms + female_terms)
        def has_target_substring(adj):
            return any(tw in adj for tw in all_target_words)
        adjectives = [adj for adj in adjectives if not␣
↪has_target_substring(adj)]

    records = []

    # 2) Loop over each adjective
    for adj in adjectives:
        if adj not in model:
            continue
```

```
        adj_vec = model[adj]

        # Gather cosine similarities with male terms
        male_sims = []
        for m in male_terms:
            if m in model:
                male_sims.append(cosine_similarity(adj_vec, model[m]))

        # Gather cosine similarities with female terms
        female_sims = []
        for f in female_terms:
            if f in model:
                female_sims.append(cosine_similarity(adj_vec, model[f]))

        # Skip if we can't compute both male and female means
        if len(male_sims) == 0 or len(female_sims) == 0:
            continue

        # Compute means
        male_mean = np.mean(male_sims)
        female_mean = np.mean(female_sims)

        # Compute bias
        bias_value = male_mean - female_mean

        records.append({
            "word": adj,
            "male_mean": male_mean,
            "female_mean": female_mean,
            "bias_value": bias_value
        })

    df_bias = pd.DataFrame(records)
    return df_bias

def compute_bias_with_pvalue(adj, male_terms, female_terms, model,␣
↪permutations=1000, seed=42):
    """
    Computes the cosine-based gender bias of an adjective relative to male and␣
↪female word sets,
    and estimates the statistical significance using a permutation test.

    Parameters
    ----------
    adj : str
        The adjective whose bias is being measured.
```

```
    male_terms : list of str
        A list of words representing the male group (e.g., ["man", "vader",␣
↪"kerel"]).

    female_terms : list of str
        A list of words representing the female group (e.g., ["vrouw",␣
↪"moeder", "meid"]).

    model : KeyedVectors or similar
        A word embedding model that supports word lookup and cosine operations␣
↪(e.g., Word2Vec or FastText).

    permutations : int, default=1000
        The number of random shuffles to perform during the permutation test.

    seed : int, default=42
        Random seed to ensure reproducibility of the permutation results.

    Returns
    -------
    real_bias : float
        The observed bias score, defined as:
        mean_cosine(adj, male_terms) - mean_cosine(adj, female_terms)

    p_value : float
        The estimated probability that a bias of this magnitude (or stronger)␣
↪could occur
        by chance if gender labels were random. Lower values indicate stronger␣
↪significance.

    Description
    -----------
    - Step 1: Compute the real (observed) bias of the adjective using cosine␣
↪similarity.
    - Step 2: Create a combined pool of male and female terms.
    - Step 3: Run `permutations` number of times:
        - Shuffle the gender labels randomly.
        - Split into fake "male" and "female" groups.
        - Compute the permuted bias score.
        - Count how many times the permuted score is greater than or equal to␣
↪the real bias.
    - Step 4: The p-value is the proportion of permutations that produced a␣
↪more extreme bias
              than the observed one.
    """
```

```
    # Ensure reproducibility
    np.random.seed(seed)

    # Step 1: Compute the real cosine-based bias score
    real_bias = compute_bias(adj, male_terms, female_terms, model)

    # Combine all gender terms into one pool to shuffle
    combined_terms = male_terms + female_terms
    num_male = len(male_terms)

    # Counter for how many permuted scores are as extreme as the real one
    extreme_count = 0

    # Step 2: Permutation loop
    for _ in range(permutations):
        np.random.shuffle(combined_terms)

        # Split shuffled terms into permuted male and female groups
        permuted_male = combined_terms[:num_male]
        permuted_female = combined_terms[num_male:]

        # Step 3: Compute bias under this random split
        permuted_bias = compute_bias(adj, permuted_male, permuted_female, model)

        # Count if the permuted bias is more extreme than the observed one
        if abs(permuted_bias) >= abs(real_bias):
            extreme_count += 1

    # Step 4: Compute the p-value as the proportion of extreme permutations
    p_value = extreme_count / permutations

    return real_bias, p_value

def tag_bias_agreement(row, alpha=0.05):
    sig_w2v = row['p_value_w2v'] < alpha
    sig_ft  = row['p_value_ft'] < alpha
    same_sign = np.sign(row['bias_w2v']) == np.sign(row['bias_ft'])

    if sig_w2v and sig_ft:
        if same_sign:
            return "Significant in both (agree)"
        else:
            return "Significant in both (oppose)"
    elif sig_w2v:
        return "Only Word2Vec"
    elif sig_ft:
```

```
        return "Only FastText"
    else:
        return "Non-significant"
```

0.3 Embedding Models

[5]:
```
################################################################################
# 1) Load FastText embeddings
################################################################################
logging.info("Loading Fasttext embeddings with Gensim from file...")
nl_embeddings = gensim.models.KeyedVectors.load_word2vec_format(
    "/Users/matthijstentije/University/MSc_Data-Science/Thesis/
↪MSc_Data_Science_Thesis/data/cc.nl.300.vec.gz",
    binary=False
)
logging.info("Fasttext embeddings loaded.")

# Convert to WEFE-compatible format
fasttext_model = WordEmbeddingModel(nl_embeddings, "Dutch FastText")
logging.info("Fasttext Embeddings Model Created.")

################################################################################
# 2) Load Word2Vec model
################################################################################
logging.info("Loading Word2Vec model from file...")
model_path = "/Users/matthijstentije/University/MSc_Data-Science/Thesis/
↪MSc_Data_Science_Thesis/data/sonar-320.txt"
model_w2v = KeyedVectors.load_word2vec_format(model_path, binary=False)
logging.info("Word2Vec Model loaded successfully.")
```

```
2025-04-09 11:32:23,033 [INFO] Loading Fasttext embeddings with Gensim from
file…
2025-04-09 11:32:23,034 [INFO] loading projection weights from
/Users/matthijstentije/University/MSc_Data-
Science/Thesis/MSc_Data_Science_Thesis/data/cc.nl.300.vec.gz
2025-04-09 11:35:05,710 [INFO] KeyedVectors lifecycle event {'msg': 'loaded
(2000000, 300) matrix of type float32 from
/Users/matthijstentije/University/MSc_Data-
Science/Thesis/MSc_Data_Science_Thesis/data/cc.nl.300.vec.gz', 'binary': False,
'encoding': 'utf8', 'datetime': '2025-04-09T11:35:05.710687', 'gensim': '4.3.3',
'python': '3.12.1 (v3.12.1:2305ca5144, Dec  7 2023, 17:23:38) [Clang 13.0.0
(clang-1300.0.29.30)]', 'platform': 'macOS-15.3.2-arm64-arm-64bit', 'event':
'load_word2vec_format'}
2025-04-09 11:35:05,712 [INFO] Fasttext embeddings loaded.
2025-04-09 11:35:05,712 [INFO] Fasttext Embeddings Model Created.
2025-04-09 11:35:05,713 [INFO] Loading Word2Vec model from file…
2025-04-09 11:35:05,713 [INFO] loading projection weights from
```

```
/Users/matthijstentije/University/MSc_Data-
Science/Thesis/MSc_Data_Science_Thesis/data/sonar-320.txt
2025-04-09 11:36:01,059 [INFO] KeyedVectors lifecycle event {'msg': 'loaded
(626711, 320) matrix of type float32 from
/Users/matthijstentije/University/MSc_Data-
Science/Thesis/MSc_Data_Science_Thesis/data/sonar-320.txt', 'binary': False,
'encoding': 'utf8', 'datetime': '2025-04-09T11:36:01.059857', 'gensim': '4.3.3',
'python': '3.12.1 (v3.12.1:2305ca5144, Dec  7 2023, 17:23:38) [Clang 13.0.0
(clang-1300.0.29.30)]', 'platform': 'macOS-15.3.2-arm64-arm-64bit', 'event':
'load_word2vec_format'}
2025-04-09 11:36:01,060 [INFO] Word2Vec Model loaded successfully.
```

0.4 Extracting Adjectives + Spacy

[6]:
```
NUMERIC_WORDS = {
    "twee", "drie", "vier", "vijf", "zes", "zeven", "acht", "negen", "tien",
    "elf", "twaalf", "dertien", "veertien", "vijftien", "zestien", "zeventien",
    "achttien", "negentien", "twintig", "dertig", "veertig", "vijftig",
    "zestig", "zeventig", "tachtig", "negentig", "honderd", "duizend"
}
```

[9]:
```
################################################################################
# 3) Load spaCy for Dutch, define function to extract adjectives
################################################################################
nlp = spacy.load('nl_core_news_lg')

def contains_numeric_word(lemma):
    return any(num in lemma for num in NUMERIC_WORDS)

def extract_adjectives_from_csv(file_path):
    """
    Leest een CSV-bestand in, parse elke phrase met spaCy,
    en retourneert unieke gelemmatiseerde bijvoeglijke naamwoorden.
    """
    logging.info(f"Loading CSV file: {file_path}")
    try:
        df = pd.read_csv(file_path, delimiter=';', usecols=[0],␣
↪names=["Group"], header=0)
        logging.info(f"CSV loaded successfully with shape: {df.shape}")
    except Exception as e:
        logging.error(f"Failed to load CSV file: {e}")
        raise

    df.dropna(subset=["Group"], inplace=True)
    logging.info(f"Dropped NaN rows. Remaining phrases: {len(df)}")

    adjectives = []
```

```
    logging.info("Starting POS tagging and lemmatization...")
    for idx, phrase in enumerate(df["Group"]):
        doc = nlp(phrase)
        for token in doc:
            if token.pos_ == "ADJ" and token.is_alpha:
                lemma = token.lemma_.lower()

                # Filter alles met tekstuele getallen behalve 'een'
                if lemma != "een" and contains_numeric_word(lemma):
                    continue
                adjectives.append(lemma)

        if idx % 1000 == 0 and idx > 0:
            logging.info(f"Processed {idx} phrases...")

    unique_adjectives = list(dict.fromkeys(adjectives))
    logging.info(f"Extracted {len(unique_adjectives)} unique adjectives.")
    return unique_adjectives

# ---- Use the function ----
csv_file_path = "/Users/matthijstentije/University/MSc_Data-Science/Thesis/
 ↪MSc_Data_Science_Thesis/data/Corpus_Hedendaags_Nederlands_Adjectives.csv"
adjectives = extract_adjectives_from_csv(csv_file_path)
                                                                                ␣
 ↪################################################################################
# 3) Load spaCy for Dutch, define function to extract adjectives
################################################################################
nlp = spacy.load('nl_core_news_lg')

def contains_numeric_word(lemma):
    return any(num in lemma for num in NUMERIC_WORDS)

def extract_adjectives_from_csv(file_path):
    """
    Leest een CSV-bestand in, parse elke phrase met spaCy,
    en retourneert unieke gelemmatiseerde bijvoeglijke naamwoorden.
    """
    logging.info(f"Loading CSV file: {file_path}")
    try:
        df = pd.read_csv(file_path, delimiter=';', usecols=[0],␣
 ↪names=["Group"], header=0)
        logging.info(f"CSV loaded successfully with shape: {df.shape}")
    except Exception as e:
        logging.error(f"Failed to load CSV file: {e}")
        raise

    df.dropna(subset=["Group"], inplace=True)
```

```python
    logging.info(f"Dropped NaN rows. Remaining phrases: {len(df)}")

    adjectives = []
    logging.info("Starting POS tagging and lemmatization...")
    for idx, phrase in enumerate(df["Group"]):
        doc = nlp(phrase)
        for token in doc:
            if token.pos_ == "ADJ" and token.is_alpha:
                lemma = token.lemma_.lower()

                # Filter alles met tekstuele getallen behalve 'een'
                if lemma != "een" and contains_numeric_word(lemma):
                    continue
                adjectives.append(lemma)

        if idx % 1000 == 0 and idx > 0:
            logging.info(f"Processed {idx} phrases...")

    unique_adjectives = list(dict.fromkeys(adjectives))
    logging.info(f"Extracted {len(unique_adjectives)} unique adjectives.")
    return unique_adjectives

# ---- Use the function ----
csv_file_path = "/Users/matthijstentije/University/MSc_Data-Science/Thesis/
 ↪MSc_Data_Science_Thesis/data/Corpus_Hedendaags_Nederlands_Adjectives.csv"
adjectives = extract_adjectives_from_csv(csv_file_path)
```

```
2025-04-09 11:38:07,106 [INFO] Loading CSV file:
/Users/matthijstentije/University/MSc_Data-Science/Thesis/MSc_Data_Science_Thesi
s/data/Corpus_Hedendaags_Nederlands_Adjectives.csv
2025-04-09 11:38:07,118 [INFO] CSV loaded successfully with shape: (19242, 1)
2025-04-09 11:38:07,121 [INFO] Dropped NaN rows. Remaining phrases: 19239
2025-04-09 11:38:07,121 [INFO] Starting POS tagging and lemmatization…
2025-04-09 11:38:08,771 [INFO] Processed 1000 phrases…
2025-04-09 11:38:10,428 [INFO] Processed 2000 phrases…
2025-04-09 11:38:12,193 [INFO] Processed 3000 phrases…
2025-04-09 11:38:13,953 [INFO] Processed 4000 phrases…
2025-04-09 11:38:15,802 [INFO] Processed 5000 phrases…
2025-04-09 11:38:17,652 [INFO] Processed 6000 phrases…
2025-04-09 11:38:19,354 [INFO] Processed 7000 phrases…
2025-04-09 11:38:21,056 [INFO] Processed 8000 phrases…
2025-04-09 11:38:22,769 [INFO] Processed 9000 phrases…
2025-04-09 11:38:24,554 [INFO] Processed 10000 phrases…
2025-04-09 11:38:26,161 [INFO] Processed 11000 phrases…
2025-04-09 11:38:28,008 [INFO] Processed 12000 phrases…
2025-04-09 11:38:29,950 [INFO] Processed 13000 phrases…
2025-04-09 11:38:32,140 [INFO] Processed 14000 phrases…
2025-04-09 11:38:34,365 [INFO] Processed 15000 phrases…
```

```
2025-04-09 11:38:36,508 [INFO] Processed 16000 phrases…
2025-04-09 11:38:38,606 [INFO] Processed 17000 phrases…
2025-04-09 11:38:40,637 [INFO] Processed 18000 phrases…
2025-04-09 11:38:42,689 [INFO] Processed 19000 phrases…
2025-04-09 11:38:43,171 [INFO] Extracted 2834 unique adjectives.
2025-04-09 11:38:45,388 [INFO] Loading CSV file:
/Users/matthijstentije/University/MSc_Data-Science/Thesis/MSc_Data_Science_Thesi
s/data/Corpus_Hedendaags_Nederlands_Adjectives.csv
2025-04-09 11:38:45,398 [INFO] CSV loaded successfully with shape: (19242, 1)
2025-04-09 11:38:45,401 [INFO] Dropped NaN rows. Remaining phrases: 19239
2025-04-09 11:38:45,401 [INFO] Starting POS tagging and lemmatization…
2025-04-09 11:38:47,476 [INFO] Processed 1000 phrases…
2025-04-09 11:38:49,483 [INFO] Processed 2000 phrases…
2025-04-09 11:38:51,495 [INFO] Processed 3000 phrases…
2025-04-09 11:38:53,607 [INFO] Processed 4000 phrases…
2025-04-09 11:38:55,573 [INFO] Processed 5000 phrases…
2025-04-09 11:38:57,473 [INFO] Processed 6000 phrases…
2025-04-09 11:38:59,436 [INFO] Processed 7000 phrases…
2025-04-09 11:39:01,370 [INFO] Processed 8000 phrases…
2025-04-09 11:39:03,293 [INFO] Processed 9000 phrases…
2025-04-09 11:39:05,250 [INFO] Processed 10000 phrases…
2025-04-09 11:39:07,224 [INFO] Processed 11000 phrases…
2025-04-09 11:39:09,145 [INFO] Processed 12000 phrases…
2025-04-09 11:39:11,114 [INFO] Processed 13000 phrases…
2025-04-09 11:39:13,017 [INFO] Processed 14000 phrases…
2025-04-09 11:39:14,993 [INFO] Processed 15000 phrases…
2025-04-09 11:39:16,891 [INFO] Processed 16000 phrases…
2025-04-09 11:39:18,845 [INFO] Processed 17000 phrases…
2025-04-09 11:39:20,759 [INFO] Processed 18000 phrases…
2025-04-09 11:39:22,919 [INFO] Processed 19000 phrases…
2025-04-09 11:39:23,813 [INFO] Extracted 2834 unique adjectives.
```

[10]:

```python
adjectives_w2v = {w for w in adjectives if w in model_w2v}
adjectives_ft  = {w for w in adjectives if w in fasttext_model}


#  Take the intersection of the two sets
union_vocab = adjectives_w2v.intersection(adjectives_ft)
print(f"Number of adjectives in Word2Vec: {len(adjectives_w2v)}")
print(f"Number of adjectives in FastText : {len(adjectives_ft)}")
print(f"Total in intersection (Word2Vec   FastText): {len(union_vocab)}")


# Exclude 'target_words' from the intersection
target_words = [
    "man", "kerel", "jongen", "vader", "zoon", "vent", "gast", "meneer",
    "opa", "oom", "vrouw", "dame", "meisje", "moeder", "dochter",
```

```
    "tante", "oma", "mevrouw", "meid",
]

filtered_adjectives = [
    adj for adj in union_vocab
    if not any(tw in adj for tw in target_words)
]
print(f"Remaining adjectives in the intersection after filtering target words:␣
  ↪{len(filtered_adjectives)}")
```

```
Number of adjectives in Word2Vec: 2675
Number of adjectives in FastText : 2685
Total in intersection (Word2Vec   FastText): 2663
Remaining adjectives in the intersection after filtering target words: 2641
```

0.5 Cosine Similarity Bias

[11]:
```
# Define your reference sets (as in your message)
MALE_WORDS = ["man", "kerel", "jongen", "vader", "zoon", "vent", "gast",␣
  ↪"meneer", "opa", "oom"]
FEMALE_WORDS = ["vrouw", "dame", "meisje", "moeder", "dochter", "tante", "oma",␣
  ↪"mevrouw", "meid"]
```

[12]:
```
# STEP 1 - WORD2VEC
logging.info("Step 1 (W2V): Computing raw cosine biases for all adjectives...")

df_indiv_bias_w2v = compute_individual_bias(
    adjectives=filtered_adjectives,
    male_terms=MALE_WORDS,
    female_terms=FEMALE_WORDS,
    model=model_w2v,
    exclude_substrings=True  # Optional, avoids words like "mannetje"
)

logging.info(f"Word2Vec: Computed raw bias for {len(df_indiv_bias_w2v)}␣
  ↪adjectives.")


# STEP 1 - FASTTEXT
logging.info("Step 1 (FastText): Computing raw cosine biases for all adjectives.
  ↪..")

df_indiv_bias_ft = compute_individual_bias(
    adjectives=filtered_adjectives,
    male_terms=MALE_WORDS,
    female_terms=FEMALE_WORDS,
    model=fasttext_model,
```

```
    exclude_substrings=True
)

logging.info(f"FastText: Computed raw bias for {len(df_indiv_bias_ft)}␣
 ↪adjectives.")
```

```
2025-04-09 11:39:23,854 [INFO] Step 1 (W2V): Computing raw cosine biases for all
adjectives…
2025-04-09 11:39:24,078 [INFO] Word2Vec: Computed raw bias for 2641 adjectives.
2025-04-09 11:39:24,078 [INFO] Step 1 (FastText): Computing raw cosine biases
for all adjectives…
2025-04-09 11:39:24,323 [INFO] FastText: Computed raw bias for 2641 adjectives.
```

[13]:

```
# STEP 2 - WORD2VEC
df_indiv_bias_w2v['abs_bias'] = df_indiv_bias_w2v['bias_value'].abs()
top_bias_words_w2v = df_indiv_bias_w2v.sort_values('abs_bias',␣
 ↪ascending=False)['word'].tolist()

# STEP 2 - FASTTEXT
df_indiv_bias_ft['abs_bias'] = df_indiv_bias_ft['bias_value'].abs()
top_bias_words_ft = df_indiv_bias_ft.sort_values('abs_bias',␣
 ↪ascending=False)['word'].tolist()

logging.info(f"most biased words (W2V):")
print(top_bias_words_w2v[:10])
logging.info(f"Most biased words (FastText):")
print(top_bias_words_ft[:10])
```

```
2025-04-09 11:39:24,334 [INFO] most biased words (W2V):
2025-04-09 11:39:24,335 [INFO] Most biased words (FastText):
```

```
['lesbisch', 'blond', 'beeldschoon', 'zwanger', 'ongepland', 'bloedmooie',
'beeldig', 'ongehuwd', 'kinderloos', 'sensueel']
['snoezig', 'beeldschoon', 'zwanger', 'mollig', 'tuttig', 'sensueel',
'genitaal', 'feminien', 'lieftallig', 'superschattig']
```

[14]:

```
# STEP 3 - WORD2VEC
logging.info(f"Step 3 (W2V): Running permutation p-value test on adjectives...")
results_w2v = []

for word in filtered_adjectives:
    try:
        bias, pval = compute_bias_with_pvalue(word, MALE_WORDS, FEMALE_WORDS,␣
 ↪model_w2v)
        results_w2v.append({'word': word, 'bias': bias, 'p_value': pval})
    except Exception as e:
        logging.warning(f"Word2Vec error on '{word}': {e}")
```

```
df_bias_sig_w2v = pd.DataFrame(results_w2v).sort_values('p_value')
logging.info(f"Word2Vec: Finished permutation testing for {len(results_w2v)}␣
↪words.")
print("\n=== Top Word2Vec Results (sorted by p-value) ===")
print(df_bias_sig_w2v.head(10))


# STEP 3 - FASTTEXT
logging.info(f"Step 3 (FastText): Running permutation p-value test on␣
↪adjectives...")
results_ft = []

for word in filtered_adjectives:
    try:
        bias, pval = compute_bias_with_pvalue(word, MALE_WORDS, FEMALE_WORDS,␣
↪fasttext_model)
        results_ft.append({'word': word, 'bias': bias, 'p_value': pval})
    except Exception as e:
        logging.warning(f"  FastText error on '{word}': {e}")

df_bias_sig_ft = pd.DataFrame(results_ft).sort_values('p_value')
logging.info(f"FastText: Finished permutation testing for {len(results_ft)}␣
↪words.")
print("\n=== Top FastText Results (sorted by p-value) ===")
print(df_bias_sig_ft.head(10))
```

```
2025-04-09 11:39:24,343 [INFO] Step 3 (W2V): Running permutation p-value test on
adjectives…
2025-04-09 11:42:43,072 [INFO] Word2Vec: Finished permutation testing for 2641
words.
2025-04-09 11:42:43,076 [INFO] Step 3 (FastText): Running permutation p-value
test on adjectives…


=== Top Word2Vec Results (sorted by p-value) ===
                 word      bias  p_value
290             knapp -0.057418    0.001
2052        statutair  0.046310    0.002
801           indisch -0.042601    0.003
627   maatschappelijk -0.042173    0.003
1981         lesbisch -0.081243    0.006
1669     alleenstaand -0.047796    0.006
2189           luther  0.058629    0.006
1989            lamme  0.040604    0.006
1282            zedig -0.046326    0.007
2355          corrupt  0.062605    0.008
```

```
2025-04-09 11:45:58,883 [INFO] FastText: Finished permutation testing for 2641
```

```
words.
```

```
=== Top FastText Results (sorted by p-value) ===
                   word      bias  p_value
2396           poezelig -0.083723      0.0
172           gortdroog  0.053274      0.0
2559            geniaal  0.082225      0.0
1922  voetbaltechnisch  0.062676      0.0
1116            slimmer  0.060725      0.0
20          interessant  0.054448      0.0
1778         hinderlijk  0.056049      0.0
667             tuttig -0.102206      0.0
1358           lieflijk -0.074286      0.0
1721            zoetig -0.045422      0.0
```

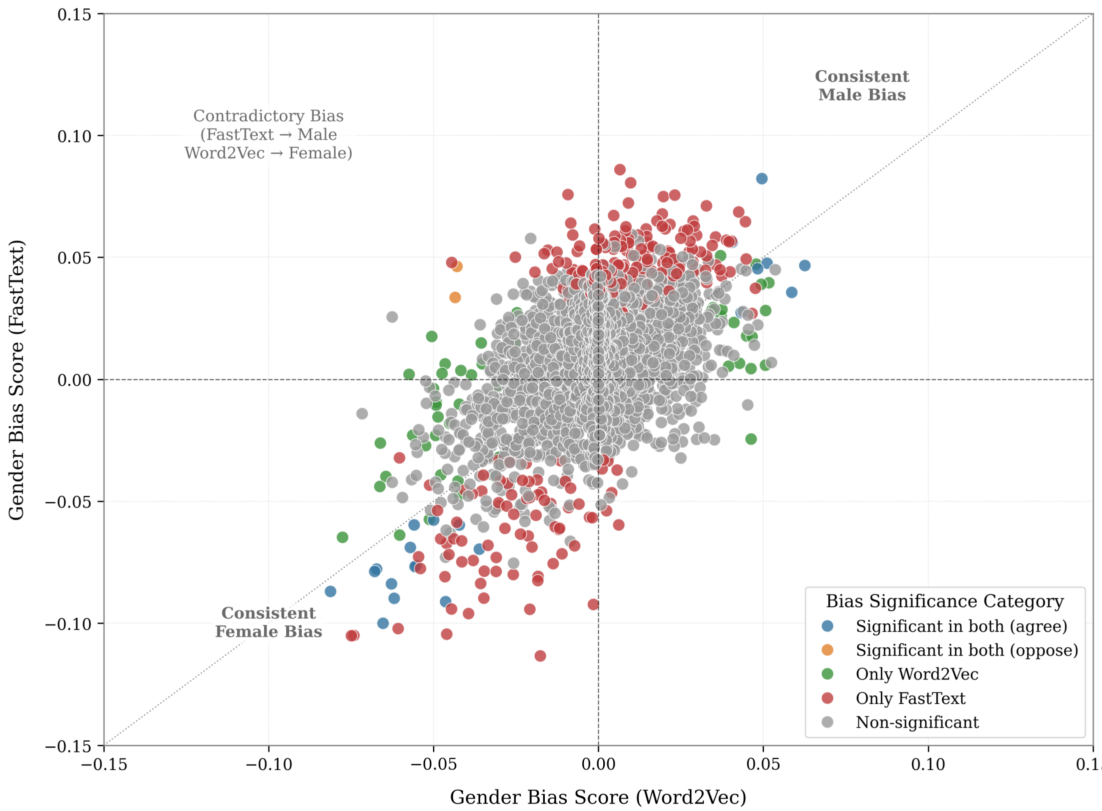
0.5.1 Metrics

[72]:
```python
# Merge on word
df_compare = pd.merge(
    df_bias_sig_w2v.rename(columns={'bias': 'bias_w2v', 'p_value':
 ↪'p_value_w2v'}),
    df_bias_sig_ft.rename(columns={'bias': 'bias_ft', 'p_value': 'p_value_ft'}),
    on='word',
    suffixes=('', '_ft')
)

# Tag each row (assuming tag_bias_agreement function is defined elsewhere)
df_compare['tag'] = df_compare.apply(tag_bias_agreement, axis=1)

# Set publication-quality parameters
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.patheffects as path_effects

plt.rcParams['font.family'] = 'serif'
plt.rcParams['font.size'] = 11
plt.rcParams['axes.linewidth'] = 0.8
plt.rcParams['xtick.major.width'] = 0.8
plt.rcParams['ytick.major.width'] = 0.8

# Create figure with appropriate dimensions for academic paper
plt.figure(figsize=(10, 8), dpi=300)

# Professional color palette (colorblind-friendly)
palette = {
    "Significant in both (agree)": "#3274A1",    # blue
    "Significant in both (oppose)": "#E1812C",   # orange
```

```
    "Only Word2Vec": "#3A923A",                   # green
    "Only FastText": "#C03D3E",                   # red
    "Non-significant": "#999999"                  # gray
}

# Create the scatterplot with professional styling
scatter = sns.scatterplot(
    data=df_compare,
    x='bias_w2v',
    y='bias_ft',
    hue='tag',
    palette=palette,
    s=60,  # Slightly smaller points for clarity
    edgecolor='white',  # White edges help distinguish overlapping points
    alpha=0.8,
    linewidth=0.5
)

# Add reference lines with improved styling
plt.axhline(0, color='black', linestyle='--', linewidth=0.7, alpha=0.6)
plt.axvline(0, color='black', linestyle='--', linewidth=0.7, alpha=0.6)
plt.plot([-0.15, 0.15], [-0.15, 0.15], linestyle=':', color='dimgray',␣
↪linewidth=0.8, alpha=0.7)  # y = x

# Quadrant labels with better positioning and formatting
quadrant_labels = [
    {"text": "Consistent\nMale Bias", "pos": (0.08, 0.12), "ha": "center",␣
↪"fontweight": "bold"},
    {"text": "Contradictory Bias\n(FastText → Male\nWord2Vec → Female)", "pos":␣
↪(-0.1, 0.1), "ha": "center", "fontweight": "normal"},
    {"text": "Consistent\nFemale Bias", "pos": (-0.1, -0.1), "ha": "center",␣
↪"fontweight": "bold"},
]

for label in quadrant_labels:
    text = plt.text(
        label["pos"][0], label["pos"][1],
        label["text"],
        fontsize=10,
        color='dimgray',
        ha=label["ha"],
        va="center",
        fontweight=label.get("fontweight", "normal"),
        bbox=dict(facecolor='white', alpha=0.7, edgecolor='none', pad=2)
    )
    # Add subtle shadow effect for better readability
```

```
    text.set_path_effects([path_effects.withStroke(linewidth=3,␣
↪foreground='white')])



# Axis labels with more professional formatting
plt.xlabel("Gender Bias Score (Word2Vec)",
           fontsize=12, labelpad=10)
plt.ylabel("Gender Bias Score (FastText)",
           fontsize=12, labelpad=10)


# Legend with better formatting and positioning
handles, labels = plt.gca().get_legend_handles_labels()
order = [
    "Significant in both (agree)",
    "Significant in both (oppose)",
    "Only Word2Vec",
    "Only FastText",
    "Non-significant"
]
ordered = sorted(zip(labels, handles), key=lambda x: order.index(x[0]))
labels, handles = zip(*ordered)

legend = plt.legend(
    handles, labels,
    title="Bias Significance Category",
    loc='lower right',
    fontsize=10,
    title_fontsize=11,
    frameon=True,
    framealpha=0.95,
    edgecolor='lightgray'
)
legend.get_frame().set_linewidth(0.8)

# Set consistent axis limits
plt.xlim(-0.15, 0.15)
plt.ylim(-0.15, 0.15)

# Add subtle grid for readability
plt.grid(True, linestyle=':', alpha=0.3, color='gray', linewidth=0.5)

# Make tick marks more readable
plt.tick_params(axis='both', which='major', labelsize=10, width=0.8, length=4)

# Add subtle axes spines
```

```python
for spine in plt.gca().spines.values():
    spine.set_linewidth(0.8)
    spine.set_color('gray')

# Improve overall layout
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

# Save high-resolution figure for publication
plt.savefig('gender_bias_agreement_plot.pdf', bbox_inches='tight', dpi=300)
plt.savefig('gender_bias_agreement_plot.png', bbox_inches='tight', dpi=300)

# Display the figure
plt.show()
```



[16]:
```python
corr, pval = pearsonr(df_compare['bias_w2v'], df_compare['bias_ft'])
print(f"Correlation (Word2Vec vs. FastText) = {corr:.3f} (p = {pval:.4g})")
```

```
Correlation (Word2Vec vs. FastText) = 0.557 (p = 2.714e-215)
```

0.5.2 Z-scores

[17]:
```
# STEP 1 - Z-scores for Word2Vec
mean_w2v = df_bias_sig_w2v['bias'].mean()
std_w2v = df_bias_sig_w2v['bias'].std()

df_bias_sig_w2v['z_score_w2v'] = (df_bias_sig_w2v['bias'] - mean_w2v) / std_w2v

# STEP 1 - Z-scores for FastText
mean_ft = df_bias_sig_ft['bias'].mean()
std_ft = df_bias_sig_ft['bias'].std()

df_bias_sig_ft['z_score_ft'] = (df_bias_sig_ft['bias'] - mean_ft) / std_ft
```

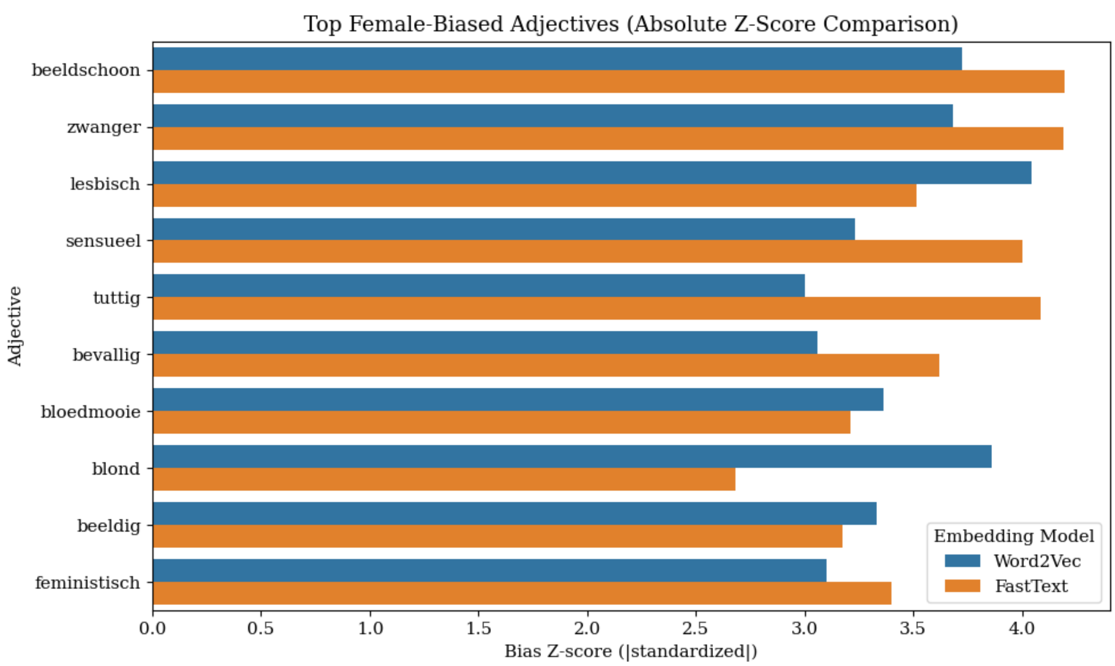
[18]:
```
# Merge on shared adjectives
df_z_compare = pd.merge(
    df_bias_sig_w2v[['word', 'z_score_w2v']],
    df_bias_sig_ft[['word', 'z_score_ft']],
    on='word'
)

# Select top N based on absolute average Z-score
df_z_compare['avg_abs_z'] = (df_z_compare['z_score_w2v'].abs() +␣
 ↪df_z_compare['z_score_ft'].abs()) / 2
df_top = df_z_compare.sort_values('avg_abs_z', ascending=False).head(15)

print("\n=== Top 15 Biased Words Across Both Models (by average Z) ===")
print(df_top[['word', 'z_score_w2v', 'z_score_ft']])
```

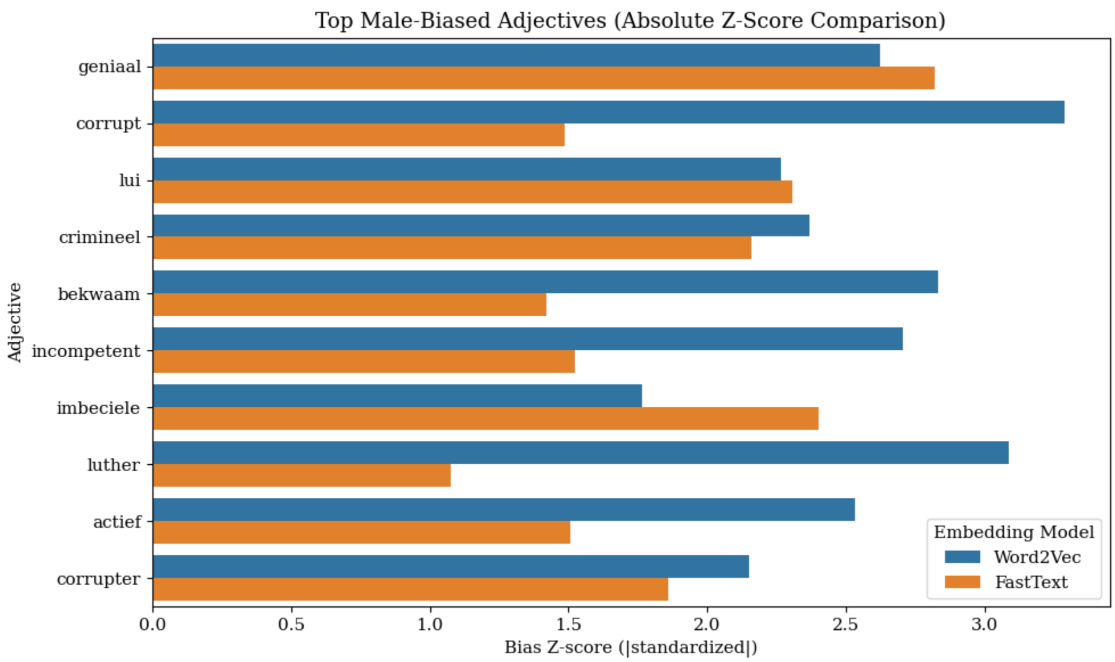
```
=== Top 15 Biased Words Across Both Models (by average Z) ===
            word  z_score_w2v  z_score_ft
119  beeldschoon    -3.722530   -4.195354
80       zwanger    -3.684167   -4.190968
4       lesbisch    -4.045882   -3.515283
46      sensueel    -3.233835   -4.003994
90        tuttig    -3.000134   -4.085640
24      bevallig    -3.061357   -3.620957
25     bloedmooie   -3.362361   -3.208645
21         blond    -3.860200   -2.684552
13      beeldig     -3.333266   -3.171831
18  feministisch    -3.103223   -3.399234
153       mollig    -2.249227   -4.171565
329    lieftallig   -2.175136   -3.785378
8          zedig    -2.265749   -3.672614
75     goudblonde   -2.739430   -3.133878
39     glamoureus   -2.717603   -3.117920
```

[19]:
```python
# Filter separately
df_male = df_z_compare[
    (df_z_compare['z_score_w2v'] > 0) & (df_z_compare['z_score_ft'] > 0)
].copy()

df_female = df_z_compare[
    (df_z_compare['z_score_w2v'] < 0) & (df_z_compare['z_score_ft'] < 0)
].copy()

# top-N limit
TOP_N = 10
df_male = df_male.sort_values('avg_abs_z', ascending=False).head(TOP_N)
df_female = df_female.sort_values('avg_abs_z', ascending=False).head(TOP_N)
```

[20]:
```python
def plot_bias_barplot_abs(df_subset, title):
    """
    Plot absolute Z-scores for bias (e.g., for female-biased words),
    so all bars go left to right.
    """
    df_plot = df_subset.copy()

    # Take absolute Z-scores
    df_plot['z_score_w2v'] = df_plot['z_score_w2v'].abs()
    df_plot['z_score_ft'] = df_plot['z_score_ft'].abs()

    # Sort by average
    df_plot['avg_z'] = (df_plot['z_score_w2v'] + df_plot['z_score_ft']) / 2
    df_plot = df_plot.sort_values('avg_z', ascending=False)

    df_melted = df_plot.melt(
        id_vars='word',
        value_vars=['z_score_w2v', 'z_score_ft'],
        var_name='Model',
        value_name='Z-score'
    )
    df_melted['Model'] = df_melted['Model'].map({
        'z_score_w2v': 'Word2Vec',
        'z_score_ft': 'FastText'
    })
    df_melted['word'] = pd.Categorical(df_melted['word'],␣
 ↪categories=df_plot['word'], ordered=True)

    plt.figure(figsize=(10, 6))
    sns.barplot(
        data=df_melted,
        y='word',
        x='Z-score',
```

```
        hue='Model',
        orient='h'
    )
    plt.title(title)
    plt.xlabel("Bias Z-score (|standardized|)")
    plt.ylabel("Adjective")
    plt.legend(title="Embedding Model", loc='lower right')
    plt.tight_layout()
    plt.show()

# Call the updated function for female-biased words
plot_bias_barplot_abs(df_female, "Top Female-Biased Adjectives (Absolute␣
 ↪Z-Score Comparison)")
plot_bias_barplot_abs(df_male, "Top Male-Biased Adjectives (Absolute Z-Score␣
 ↪Comparison)")
```





0.6 RIPA

[21]:
```
class GensimDutchEmbeddingModel(WordEmbeddingModel):
    def __init__(self, keyed_vectors):
        super().__init__(wv=keyed_vectors)
w2v_model = GensimDutchEmbeddingModel(model_w2v)
```

[22]:
```
# Define the query
query = Query(
    target_sets=[
        ["man", "kerel", "jongen", "vader", "zoon", "vent", "meneer", "opa",␣
↪"oom"],
        ["vrouw", "dame", "meisje", "moeder", "dochter", "tante", "oma",␣
↪"mevrouw", "meid"]],
    attribute_sets=[adjectives],
    target_sets_names=["Male Terms", "Female Terms"],
    attribute_sets_names=["Adjectives"],
)

ripa = RIPA()
result_ripa_w2v = ripa.run_query(query, w2v_model)
result_ripa_ft = ripa.run_query(query, fasttext_model)
```

[23]:
```
# 'result["word_values"]' {woord: {'mean': x, 'std': y}, ...}
df_ripa_w2v = pd.DataFrame({
```

```
    'Word': result_ripa_w2v["word_values"].keys(),
    'Mean Score': [val['mean'] for val in result_ripa_w2v["word_values"].
 ↪values()],
    'Std Dev': [val['std'] for val in result_ripa_w2v["word_values"].values()],
})

search_words = ["sterk", "zacht", "moedig", "emotioneel", "dominant",
                "zorgzaam", "aardig", "knap", "schattig"]

# Sorteer op Mean Score (die RIPA per woord toekent) en bekijk
df_ripa_w2v = df_ripa_w2v.sort_values(by="Mean Score", ascending=False).
 ↪reset_index(drop=True)

df_ripa_ft = pd.DataFrame({
    'Word': result_ripa_ft["word_values"].keys(),
    'Mean Score': [val['mean'] for val in result_ripa_ft["word_values"].
 ↪values()],
    'Std Dev': [val['std'] for val in result_ripa_ft["word_values"].values()],
})


# Sorteer op Mean Score (die RIPA per woord toekent) en bekijk
df_ripa_w2v = df_ripa_w2v.sort_values(by="Mean Score", ascending=False).
 ↪reset_index(drop=True)
df_ripa_ft = df_ripa_ft.sort_values(by="Mean Score", ascending=False).
 ↪reset_index(drop=True)
```

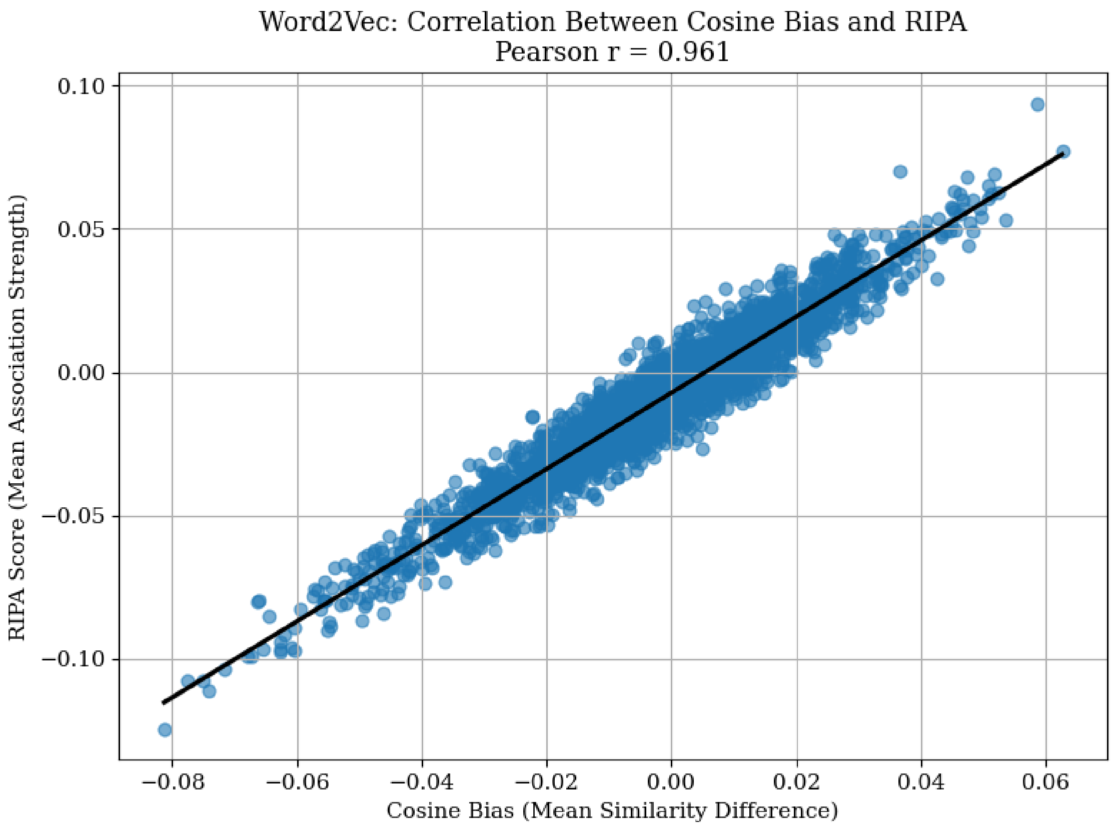
[24]:
```
# Z-score
mean_of_scores_w2v = df_ripa_w2v["Mean Score"].mean()
std_of_scores_w2v = df_ripa_w2v["Mean Score"].std()
df_ripa_w2v["Z-Score"] = (df_ripa_w2v["Mean Score"] - mean_of_scores_w2v) /␣
 ↪std_of_scores_w2v
df_ripa_w2v = df_ripa_w2v.sort_values("Z-Score", ascending=False).
 ↪reset_index(drop=True)


mean_of_scores_ft = df_ripa_ft["Mean Score"].mean()
std_of_scores_ft = df_ripa_ft["Mean Score"].std()
df_ripa_ft["Z-Score"] = (df_ripa_ft["Mean Score"] - mean_of_scores_ft) /␣
 ↪std_of_scores_ft
df_ripa_ft = df_ripa_ft.sort_values("Z-Score", ascending=False).
 ↪reset_index(drop=True)
```

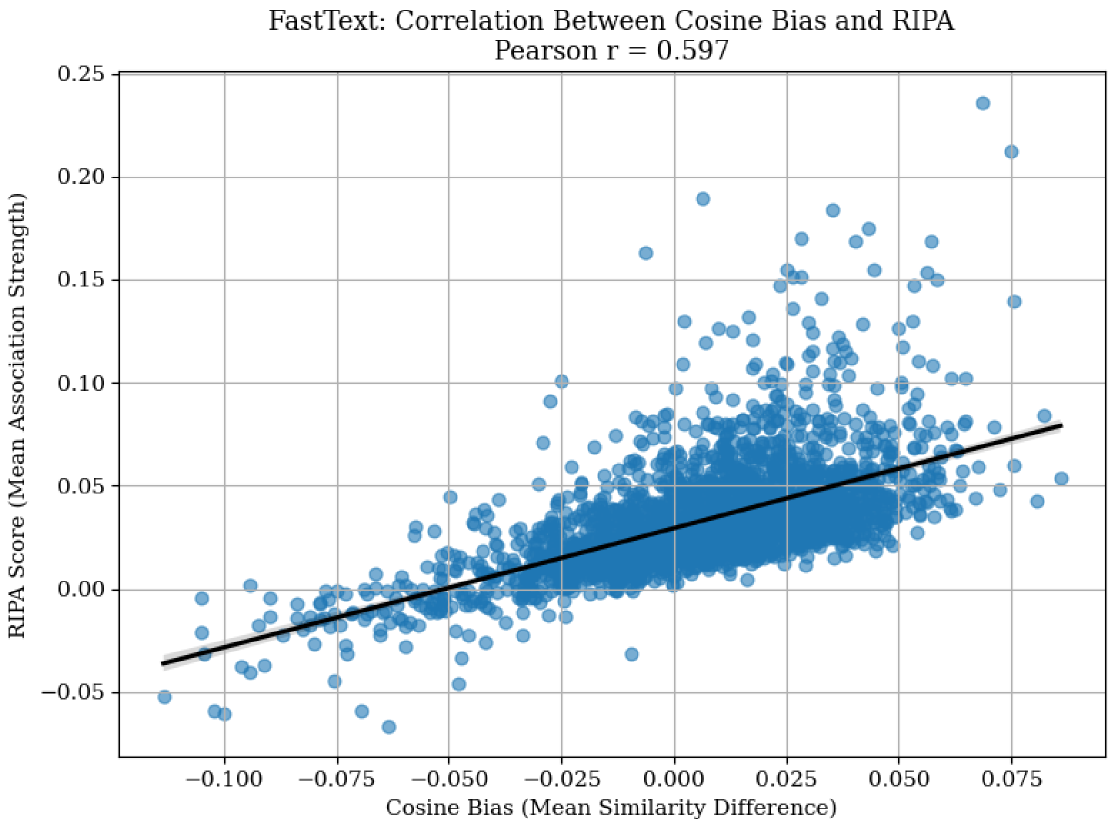
[25]:
```
def prepare_bias_comparison(df_cosine, df_ripa):
    """
```

```
    Merge cosine similarity bias with RIPA scores, compute Z-scores, and return␣
↪full merged DataFrame.
    """
    df = pd.merge(
        df_cosine,
        df_ripa[['Word', 'Mean Score']],
        left_on='word',
        right_on='Word',
        how='inner'
    ).rename(columns={'Mean Score': 'RIPA_score'})

    # Z-score normalize both metrics
    df['cosine_bias_z'] = (df['bias'] - df['bias'].mean()) / df['bias'].std()
    df['ripa_z'] = (df['RIPA_score'] - df['RIPA_score'].mean()) /␣
↪df['RIPA_score'].std()

    return df.drop(columns='Word')
# Assume you have:
# - df_bias_pval_w2v
# - df_ripa_w2v
# - df_bias_pval_ft
# - df_ripa_ft

df_combined_w2v = prepare_bias_comparison(df_bias_sig_w2v, df_ripa_w2v)
df_combined_ft  = prepare_bias_comparison(df_bias_sig_ft, df_ripa_ft)
```

[26]:
```
import scipy.stats as stats
def plot_bias_correlation(df, model_name):
    corr, p_val = stats.pearsonr(df['bias'], df['RIPA_score'])

    plt.figure(figsize=(8, 6))
    sns.regplot(
        x='bias',
        y='RIPA_score',
        data=df,
        scatter_kws={'alpha': 0.6, 's': 40},
        line_kws={'color': 'black'}
    )
    plt.title(
        f"{model_name}: Correlation Between Cosine Bias and RIPA\n"
        f"Pearson r = {corr:.3f}",
        fontsize=13
    )
    plt.xlabel("Cosine Bias (Mean Similarity Difference)", fontsize=11)
    plt.ylabel("RIPA Score (Mean Association Strength)", fontsize=11)
    plt.grid(True)
    plt.tight_layout()
```

```
    plt.show()

plot_bias_correlation(df_combined_w2v, "Word2Vec")
plot_bias_correlation(df_combined_ft, "FastText")
```





[27]:
```
from scipy.stats import pearsonr
import pandas as pd

# Calculate correlations
r_w2v, p_w2v = pearsonr(df_combined_w2v['bias'], df_combined_w2v['RIPA_score'])
r_ft, p_ft   = pearsonr(df_combined_ft['bias'], df_combined_ft['RIPA_score'])

summary = pd.DataFrame({
    'Model': ['Word2Vec', 'FastText'],
    'r (Pearson)': [round(r_w2v, 3), round(r_ft, 3)],
    'N (words)': [len(df_combined_w2v), len(df_combined_ft)]
})

summary
```

[27]:

	Model	r (Pearson)	N (words)
0	Word2Vec	0.961	2641
1	FastText	0.597	2641

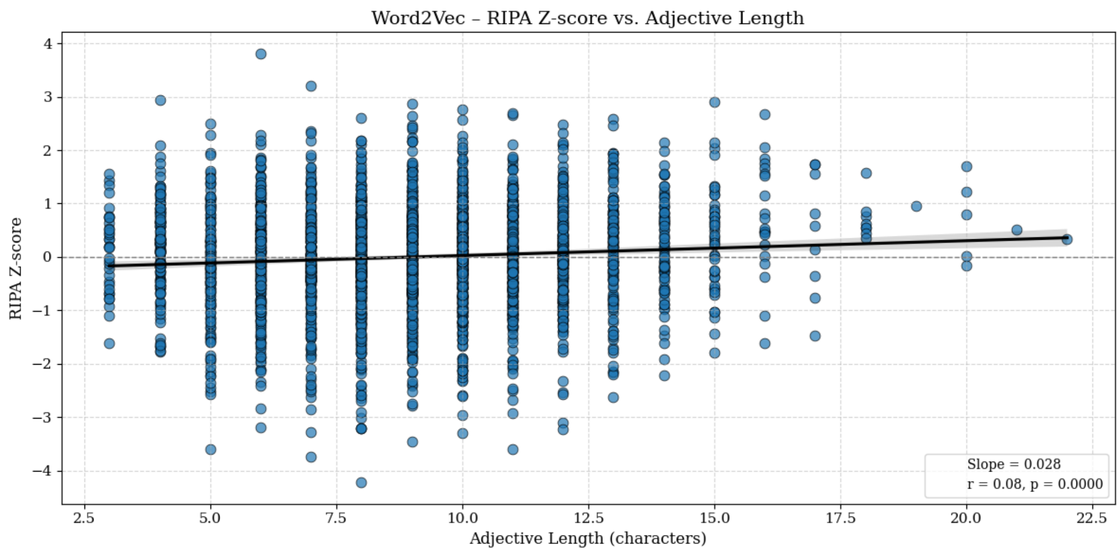
[28]:
```
# Consistent (low diff) vs inconsistent (high diff)
df_combined_w2v['abs_diff'] = abs(df_combined_w2v['cosine_bias_z'] -
  ↪df_combined_w2v['ripa_z'])
df_combined_ft['abs_diff']  = abs(df_combined_ft['cosine_bias_z'] -
  ↪df_combined_ft['ripa_z'])

print("\n--- Top 5 Most Consistent (W2V) ---")
print(df_combined_w2v.sort_values('abs_diff').head(5)[['word', 'cosine_bias_z',
  ↪'ripa_z']])

print("\n--- Top 5 Most Divergent (W2V) ---")
print(df_combined_w2v.sort_values('abs_diff', ascending=False).head(5)[['word',
  ↪'cosine_bias_z', 'ripa_z']])
```

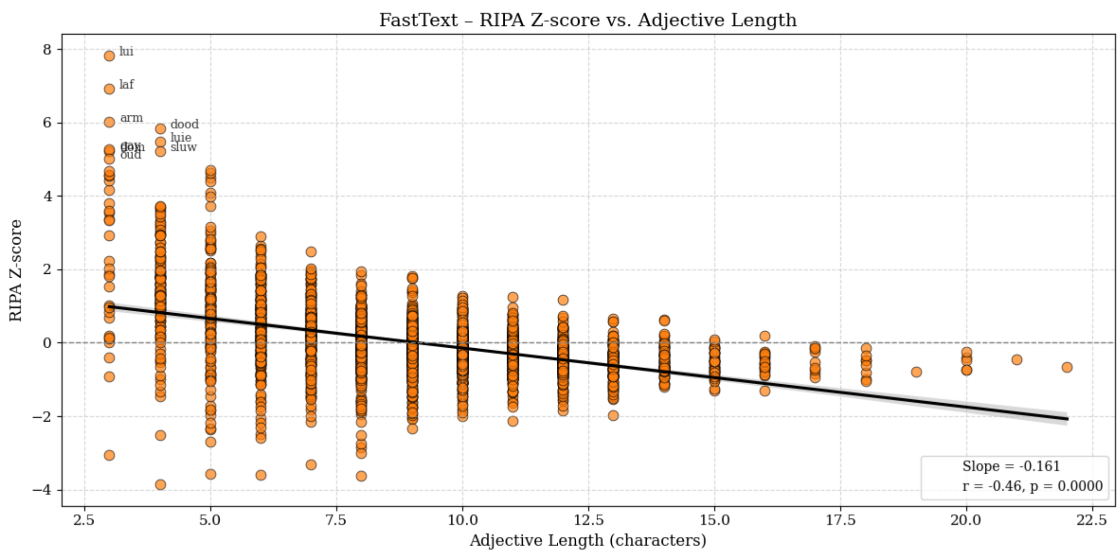
```
--- Top 5 Most Consistent (W2V) ---
              word  cosine_bias_z    ripa_z
1809      studieus       0.437570  0.437422
578      eenzijdig      -0.573615 -0.573202
18    feministisch      -3.103223 -3.103759
82       bruikbaar       1.610075  1.610624
2354  afzichtelijk       0.274938  0.274263

--- Top 5 Most Divergent (W2V) ---
                word  cosine_bias_z    ripa_z
1104            dood       1.958014  2.948446
2261           toffe       0.348041 -0.634290
2337    uiteindelijk       0.275752  1.222633
1946  overeenkomstig      -0.171883  0.741151
2232      geestelijke       0.367558  1.273814
```

[29]:
```
from scipy.stats import linregress

df_combined_w2v['adjective_length'] = df_combined_w2v['word'].str.len()
df_combined_ft['adjective_length'] = df_combined_ft['word'].str.len()

def get_ripa_regression_stats(df):
    slope, intercept, r_value, p_value, _ = linregress(df['adjective_length'],
  ↪df['ripa_z'])
    return slope, intercept, r_value, p_value

def plot_ripa_vs_length_with_stats(df, model_name, color):
    # Get regression stats
    slope, intercept, r, p = get_ripa_regression_stats(df)

    plt.figure(figsize=(12, 6))
```

```python
# --- Scatter plot
sns.scatterplot(
    data=df,
    x='adjective_length',
    y='ripa_z',
    alpha=0.7,
    color=color,
    s=60,
    edgecolor='black'
)

# --- Regression line manually
sns.regplot(
    data=df,
    x='adjective_length',
    y='ripa_z',
    scatter=False,
    color='black'
)

# --- Add regression stats to legend
plt.plot([], [], ' ', label=f"Slope = {slope:.3f}")
plt.plot([], [], ' ', label=f"r = {r:.2f}, p = {p:.4f}")

# --- Reference line
plt.axhline(0, color='gray', linestyle='--', linewidth=1)

# --- Annotate strong outliers
outliers = df[df['ripa_z'].abs() > 5]
for _, row in outliers.iterrows():
    plt.text(
        row['adjective_length'] + 0.2,
        row['ripa_z'],
        row['word'],
        fontsize=9,
        alpha=0.8
    )

# --- Layout and labels
plt.title(f"{model_name} - RIPA Z-score vs. Adjective Length", fontsize=14)
plt.xlabel("Adjective Length (characters)", fontsize=12)
plt.ylabel("RIPA Z-score", fontsize=12)
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend(loc='lower right', fontsize=10, frameon=True)
plt.tight_layout()
plt.show()
```

```python
plot_ripa_vs_length_with_stats(df_combined_w2v, "Word2Vec", "#1f77b4")
plot_ripa_vs_length_with_stats(df_combined_ft, "FastText", "#ff7f0e")
```





[30]:
```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

# Prepare aligned data
X_w2v = df_combined_w2v[['bias']].values
```

```python
X_ft  = df_combined_ft[['bias']].values
y_w2v = df_combined_w2v['RIPA_score'].values
y_ft  = df_combined_ft['RIPA_score'].values

# Fit models
model_w2v = LinearRegression().fit(X_w2v, y_w2v)
model_ft  = LinearRegression().fit(X_ft, y_ft)

# R² scores
r2_w2v = model_w2v.score(X_w2v, y_w2v)
r2_ft  = model_ft.score(X_ft, y_ft)

print(f"Word2Vec R²:  {r2_w2v:.3f}")
print(f"FastText R²:  {r2_ft:.3f}")
```

```
Word2Vec R²:  0.923
FastText R²:  0.357
```

To assess the consistency of bias detection across embedding models and metrics, we conducted a robustness analysis comparing three different operationalizations of gender bias:

Cosine similarity bias (Word2Vec) Cosine similarity bias (FastText) RIPA scores (Word2Vec) We extracted the top 50 adjectives with the highest absolute bias scores from each method and visualized their overlap using a Venn diagram (see Figure X). This allows us to assess how frequently different methods agree on which adjectives are the most gender-biased.

Key Observations:

The intersection of all three methods identified n = XX adjectives, indicating a moderate level of consensus. A large portion of the FastText cosine bias words (n = 35) were not found among the most biased terms in either of the Word2Vec-based methods, suggesting model-specific sensitivities. The overlap between Word2Vec cosine and RIPA was substantially higher (n = 28), indicating strong internal consistency within that model. This pattern supports our earlier finding that Word2Vec correlates more strongly with RIPA scores ($r = 0.96$, $p < .001$) than FastText does ($r = 0.54$), further reinforcing the idea that Word2Vec provides more stable and interpretable bias signals in this context.

Interpretation:

These results suggest that the choice of embedding model can substantially affect which words are flagged as gender-biased. While RIPA and cosine similarity are both derived from the same semantic space, their different formulations lead to partially overlapping but distinct outcomes.

FastText's low overlap and weaker correlation with RIPA may be due to:

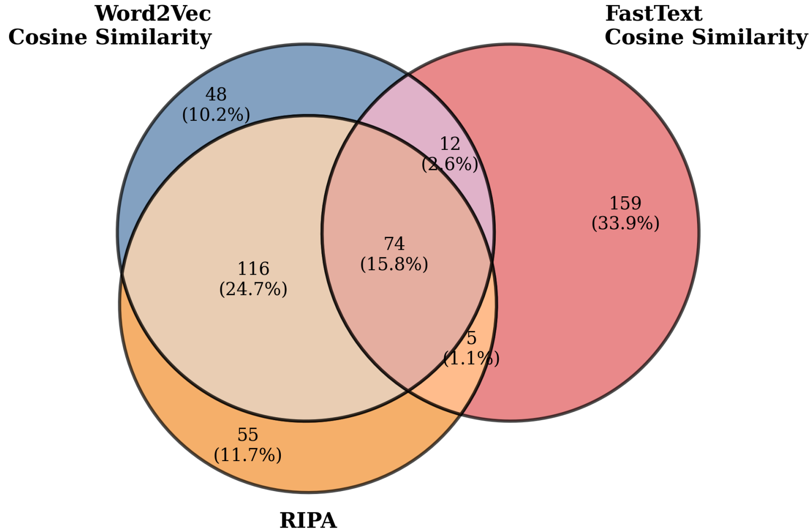
its reliance on subword-level representations, overgeneralization in morphologically complex adjectives, or differences in frequency sensitivity. Conclusion:

For downstream tasks requiring high-confidence bias detection, relying on consensus across multiple methods — or on more internally consistent models such as Word2Vec — provides a more robust foundation. The Venn analysis highlights both agreement and divergence, offering transparency in bias attribution and helping identify which adjectives consistently carry strong gender connotations across techniques.

Figure X: Venn diagram illustrating the overlap between the top 50 gender-biased adjectives as identified by three methods: cosine similarity in Word2Vec embeddings, cosine similarity in FastText embeddings, and RIPA scores in Word2Vec. Each circle represents the set of adjectives ranked highest by absolute bias scores in that method. The intersection shows the degree of agreement across models and metrics. Numbers indicate the count and percentage of adjectives that appear in each overlap region. The central region (n = 11) reflects consensus across all approaches, suggesting robust gender association signals. Non-overlapping regions reveal method-specific biases, especially from FastText, which shows low overlap with both Word2Vec-based measures.

[71]:
```
import matplotlib.pyplot as plt
from matplotlib_venn import venn3
import matplotlib.font_manager as fm
import numpy as np

TOP_N = 250

top_cosine_w2v = set(df_combined_w2v.sort_values('cosine_bias_z', key=abs,␣
 ↪ascending=False).head(TOP_N)['word'])
top_cosine_ft = set(df_combined_ft.sort_values('cosine_bias_z', key=abs,␣
 ↪ascending=False).head(TOP_N)['word'])
top_ripa_w2v = set(df_combined_w2v.sort_values('ripa_z', key=abs,␣
 ↪ascending=False).head(TOP_N)['word'])

all_words = top_cosine_w2v | top_cosine_ft | top_ripa_w2v
total_words = len(all_words)

plt.rcParams['font.family'] = 'serif'
plt.rcParams['font.size'] = 11
plt.rcParams['axes.linewidth'] = 0.8
plt.rcParams['xtick.major.width'] = 0.8
plt.rcParams['ytick.major.width'] = 0.8

fig, ax = plt.subplots(figsize=(9, 6), dpi=300)
venn = venn3(
    [top_cosine_w2v, top_cosine_ft, top_ripa_w2v],
    set_labels=("Word2Vec\nCosine Similarity", "FastText\nCosine Similarity",␣
 ↪"RIPA"),
    set_colors=("#4E79A7", "#E15759", "#F28E2B"),
    alpha=0.7,
    ax=ax
)

# Forcefully center diagram within the axis by adjusting limits
ax.set_xlim(-1.2, 1.2)
ax.set_ylim(-0.7, 0.7)
```

```python
# Bold circle edges
for patch in venn.patches:
    if patch:
        patch.set_linewidth(1.8)
        patch.set_edgecolor('black')

# Enhance label visibility and formatting
for text in venn.set_labels:
    if text:
        text.set_fontweight('bold')
        text.set_fontsize(12)

# Add percentages to each region with improved formatting
for subset_id in ['100', '010', '110', '001', '101', '011', '111']:
    subset = venn.get_label_by_id(subset_id)
    if subset:
        count = int(subset.get_text())
        perc = 100 * count / total_words
        subset.set_text(f"{count}\n({perc:.1f}%)")
        subset.set_fontsize(10)

# NOTE: Title and subtitle removed so you can add them manually as requested

# Add figure caption manually later - not in plot
# Optional grid and border
plt.grid(False)
plt.gca().spines['top'].set_visible(True)
plt.gca().spines['right'].set_visible(True)
plt.gca().spines['bottom'].set_visible(True)
plt.gca().spines['left'].set_visible(True)

plt.tight_layout(rect=[0, 0.05, 1, 0.95])

plt.savefig('gender_bias_venn_diagram.pdf', bbox_inches='tight', dpi=300)
plt.savefig('gender_bias_venn_diagram.png', bbox_inches='tight', dpi=300)

plt.show()
```



[59]:

```
shared_all = top_cosine_w2v & top_cosine_ft & top_ripa_w2v
only_in_ripa = top_ripa_w2v - (top_cosine_w2v | top_cosine_ft)
print(shared_all)
print(only_in_ripa)
```

```
{'beeldschoon', 'transseksueel', 'erotische', 'hangerig', 'dromerig',
'levenslustig', 'sluw', 'slanke', 'crimineel', 'fleurig', 'alleenstaand',
'appetijtelijk', 'bloedmooie', 'schattig', 'halfnaakt', 'goudblonde',
'rimpelig', 'platinablond', 'rozig', 'zedig', 'lief', 'flirterig', 'weelderig',
'kittig', 'zoetig', 'lieftallig', 'bevallig', 'erotisch', 'glamoureus',
'gracieus', 'vaginaal', 'geniaal', 'teder', 'lesbisch', 'ongetrouwd',
'donkerharig', 'superslank', 'zwoel', 'bloedmooi', 'naakt', 'roodharig',
'loyaal', 'superslanke', 'hoogblond', 'huishoudelijk', 'blond', 'overmoedig',
'supergezellig', 'verrukkelijk', 'sensueel', 'beeldig', 'voluptueus', 'lamme',
'modieus', 'corrupter', 'elegant', 'aanbiddelijk', 'bekoorlijk', 'indisch',
'mollig', 'huwelijks', 'spierwit', 'zwanger', 'fanatiek', 'slonzig',
'modebewust', 'slank', 'wellustig', 'goudblond', 'feministisch', 'laffe',
'ongehuwd', 'donkerblond', 'tuttig'}
{'opblaasbaar', 'bangig', 'feestelijk', 'ongrondwettig', 'spontaan',
'geelgroen', 'vleugellamme', 'bovenmenselijk', 'alledaags', 'behaaglijk',
'civiel', 'communistisch', 'onvindbaar', 'reddeloos', 'onvermurwbaar',
'benauwd', 'moordend', 'medeverantwoordelijk', 'sfeervol', 'gloednieuw',
'onaantastbaar', 'fataal', 'spoorloos', 'autoloos', 'moreel', 'literair',
'indirect', 'corruptste', 'hard', 'gedesillusioneerd', 'sterfelijk',
'aantrekkelijk', 'daadwerkelijk', 'jeugdig', 'ondoorgrondelijk', 'opdringerig',
'vermoedelijk', 'wiebelig', 'blanke', 'toornig', 'nazistisch', 'feodaal',
```

```
'precies', 'getint', 'rechtmatig', 'autocratisch', 'onkreukbaar', 'ongewenst',
'pretentieloos', 'geweldloos', 'wuft', 'deugdzaam', 'standrechtelijk',
'straffeloos', 'veelkoppig'}
```

[76]:
```
def get_top_gender_biased_words(df, top_n=25, method='combined'):
    """
    Returns top N male- and female-biased adjectives based on both cosine and␣
↪RIPA z-scores.

    Parameters
    ----------
    df : pd.DataFrame
        DataFrame with columns ['word', 'cosine_bias_z', 'ripa_z']
    top_n : int
        Number of top biased adjectives to return for each gender
    method : str
        Scoring method: 'combined', 'ripa', 'cosine', or 'borda'

    Returns
    -------
    df_male_top : Top N male-biased adjectives
    df_female_top : Top N female-biased adjectives
    """
    df = df.copy()

    if method == 'combined':
        df['score'] = (df['cosine_bias_z'] + df['ripa_z']) / 2

    elif method == 'borda':
        df['rank_cosine'] = df['cosine_bias_z'].rank(ascending=False)
        df['rank_ripa'] = df['ripa_z'].rank(ascending=False)
        df['score'] = df['rank_cosine'] + df['rank_ripa']

    elif method == 'ripa':
        df['score'] = df['ripa_z']

    elif method == 'cosine':
        df['score'] = df['cosine_bias_z']

    else:
        raise ValueError("Method must be 'combined', 'borda', 'ripa', or␣
↪'cosine'")

    # Sort by final score (desc → male bias; asc → female bias)
    df_male = df.sort_values('score', ascending=False).head(top_n)
    df_female = df.sort_values('score', ascending=True).head(top_n)
```

```
    return df_male[['word', 'cosine_bias_z', 'ripa_z', 'score']],␣
↪df_female[['word', 'cosine_bias_z', 'ripa_z', 'score']]


male_top_w2v, female_top_w2v = get_top_gender_biased_words(df_combined_w2v,␣
↪top_n=25, method='combined')

print("Top 15 Male-Biased Adjectives (Word2Vec + RIPA):")
print(male_top_w2v)

print("\nTop 15 Female-Biased Adjectives (Word2Vec + RIPA):")
print(female_top_w2v)
```

```
Top 15 Male-Biased Adjectives (Word2Vec + RIPA):
                   word  cosine_bias_z    ripa_z     score
6                luther       3.085155  3.808822  3.446988
9               corrupt       3.287878  3.201038  3.244458
61      onoverwinnelijk       2.731618  2.908050  2.819834
85     plaatsvervangend       2.771570  2.675164  2.723367
20            impopulair      2.679160  2.761592  2.720376
183            goddeloos      2.507321  2.877223  2.692272
54           incompetent      2.703911  2.650272  2.677091
45              misdadig      2.681519  2.596465  2.638992
132              bekwaam      2.830790  2.323610  2.577200
131           sadistisch      2.560351  2.575174  2.567763
384          gewetenloos      2.408697  2.690655  2.549676
67             steenrijk      2.455604  2.640475  2.548039
62          vooraanstaand     2.613492  2.469589  2.541540
43          voortvluchtig     2.472851  2.584405  2.528628
22               geniaal      2.624081  2.359347  2.491714
77             planmatig      2.471741  2.465173  2.468457
1104                dood      1.958014  2.948446  2.453230
138                rebel      2.376510  2.490010  2.433260
17          islamistisch      2.387436  2.474061  2.430748
1              statutair      2.457087  2.394643  2.425865
101            schatrijk      2.404824  2.423142  2.413983
29                actief      2.534205  2.283873  2.409039
71               capabel      2.558070  2.169800  2.363935
167            overmoedig     2.381030  2.271221  2.326126
30          operationeel      2.278166  2.328065  2.303115

Top 15 Female-Biased Adjectives (Word2Vec + RIPA):
             word  cosine_bias_z    ripa_z     score
4        lesbisch      -4.045882 -4.222666 -4.134274
21          blond      -3.860200 -3.604211 -3.732205
80        zwanger      -3.684167 -3.739871 -3.712019
119   beeldschoon      -3.722530 -3.603561 -3.663045
```

```
117     ongepland      -3.556604 -3.463500 -3.510052
25     bloedmooie      -3.362361 -3.294296 -3.328329
13        beeldig      -3.333266 -3.284909 -3.309088
46       sensueel      -3.233835 -3.210375 -3.222105
204  platinablond      -3.091807 -3.232549 -3.162179
254      voorlijk      -3.092482 -3.210495 -3.151489
18   feministisch      -3.103223 -3.103759 -3.103491
88       stijlvol      -2.979713 -3.215151 -3.097432
90         tuttig      -3.000134 -3.187600 -3.093867
24       bevallig      -3.061357 -3.011075 -3.036216
16      huwelijks      -3.189070 -2.781381 -2.985226
57    donkerharig      -2.976514 -2.931654 -2.954084
53       ongehuwd      -3.283072 -2.589211 -2.936141
70     kinderloos      -3.275023 -2.584049 -2.929536
39     glamoureus      -2.717603 -2.970243 -2.843923
157      rimpelig      -2.933284 -2.694153 -2.813718
92       erotisch      -2.684212 -2.907542 -2.795877
110       kleurig      -2.705265 -2.848998 -2.777132
40    zilvergrijs      -2.775079 -2.685033 -2.730056
0           knapp      -2.831222 -2.514538 -2.672880
48          rozig      -2.752806 -2.572354 -2.662580
```

[74]:

```python
male_top_w2v['word'].to_csv("top_male_biased_adjectives_w2v.csv", index=False,␣
 ↪header=False)
female_top_w2v['word'].to_csv("top_female_biased_adjectives_w2v.csv",␣
 ↪index=False, header=False)

print("Saved to:")
print("top_male_biased_adjectives_w2v.csv")
print("top_female_biased_adjectives_w2v.csv")
```

```
Saved to:
top_male_biased_adjectives_w2v.csv
top_female_biased_adjectives_w2v.csv
```

[35]:

```python
##################################################
# 3) Define the ML-EAT functions
##################################################
def compute_association(w: np.ndarray, A: np.ndarray) -> float:
    """
    Computes the average cosine similarity between a single vector w
    and all vectors in the set A.
    """
    return np.mean([cosine_similarity(w, a) for a in A])

def compute_attribute_association(X: np.ndarray, A: np.ndarray) -> np.ndarray:
    """
    For each vector x in X, compute the average similarity with vectors in A.
```

```
    Returns a 1D array of association scores.
    """
    return np.array([compute_association(x, A) for x in X])

def compute_attribute_association_L2(A: np.ndarray, T: np.ndarray) -> np.
 ↪ndarray:
    """
    For each vector a in A, compute the average similarity with vectors in T.
    Returns a 1D array of association scores.
    """
    return np.array([compute_association(a, T) for a in A])

def compute_joint_std(X_Associations: np.ndarray, Y_Associations: np.ndarray)␣
 ↪-> float:
    """
    Computes the pooled standard deviation of the two sets of associations.
    """
    return np.std(np.concatenate([X_Associations, Y_Associations]), ddof=1)

def compute_p_value(X_Diff: np.ndarray,
                    Y_Diff: np.ndarray,
                    permutations: int = 1000) -> float:
    """
    Uses a permutation test (randomly shuffling the X and Y labels)
    to estimate the p-value of the observed difference in sums.
    """
    # Observed difference in sums
    test_statistic = np.sum(X_Diff) - np.sum(Y_Diff)

    # Generate the empirical distribution via permutations
    combined = np.concatenate([X_Diff, Y_Diff])
    empirical_distribution = np.array([
        np.random.choice(combined,
                         size=len(X_Diff) + len(Y_Diff),
                         replace=False)
        for _ in range(permutations)
    ])

    # For each permutation, split back into "X-like" vs. "Y-like" slices
    empirical_differences = (
        np.sum(empirical_distribution[:, :len(X_Diff)], axis=1)
        - np.sum(empirical_distribution[:, len(X_Diff):], axis=1)
    )

    # Compare observed statistic to empirical distribution
    return 1 - norm.cdf(
        test_statistic,
```

```
        loc=np.mean(empirical_differences),
        scale=np.std(empirical_differences, ddof=1)
    )

def level_1(X: np.ndarray,
            Y: np.ndarray,
            A: np.ndarray,
            B: np.ndarray,
            permutations: int = 1000) -> tuple[float, float]:
    """
    Level 1 test: Compare differences in association with A vs. B
    for groups X and Y, then compute an effect size and p-value.
    """
    # For group X
    X_Associations_A = compute_attribute_association(X, A)
    X_Associations_B = compute_attribute_association(X, B)
    X_Differential_Associations = X_Associations_A - X_Associations_B

    # For group Y
    Y_Associations_A = compute_attribute_association(Y, A)
    Y_Associations_B = compute_attribute_association(Y, B)
    Y_Differential_Associations = Y_Associations_A - Y_Associations_B

    # Mean difference
    X_Mean = np.mean(X_Differential_Associations)
    Y_Mean = np.mean(Y_Differential_Associations)

    # Permutation-based p-value
    p_value = compute_p_value(X_Differential_Associations,
                              Y_Differential_Associations,
                              permutations=permutations)

    # Effect size: difference in means, normalized by joint std
    effect_size = (
        (X_Mean - Y_Mean)
        / compute_joint_std(X_Differential_Associations,␣
↪Y_Differential_Associations)
    )
    return effect_size, p_value

def level_2(T: np.ndarray,
            A: np.ndarray,
            B: np.ndarray,
            permutations: int = 1000) -> tuple[float, float]:
    """
    Level 2 test: For the group T, compare associations with A vs. B,
    returning an effect size and p-value.
```

```
    """
    A_Associations_T = compute_attribute_association_L2(A, T)
    B_Associations_T = compute_attribute_association_L2(B, T)

    p_value = compute_p_value(A_Associations_T,
                              B_Associations_T,
                              permutations=permutations)

    effect_size = (
        (np.mean(A_Associations_T) - np.mean(B_Associations_T))
        / compute_joint_std(A_Associations_T, B_Associations_T)
    )
    return effect_size, p_value

def level_3(T: np.ndarray, A: np.ndarray) -> tuple[float, float]:
    """
    Level 3 test: For the group T, measure the overall average similarity to A
    (and its standard deviation).
    """
    T_Associations_A = [cosine_similarity(t, a) for t in T for a in A]
    return np.mean(T_Associations_A), np.std(T_Associations_A, ddof=1)

def ML_EAT(A: np.ndarray,
           B: np.ndarray,
           X: np.ndarray,
           Y: np.ndarray,
           permutations: int = 1000) -> dict:
    """
    Consolidates the Level 1, Level 2, and Level 3 ML-EAT metrics into one dict.
    X, Y = two target groups you want to compare (e.g. male-coded vs.␣
 ↪female-coded words)
    A, B = two attribute sets (e.g. pleasant vs. unpleasant terms)
    """
    # --- Level 1
    L1_effect_size, L1_p_value = level_1(X, Y, A, B, permutations=permutations)

    # --- Level 2
    L2_effect_size_X, L2_p_value_X = level_2(X, A, B, permutations=permutations)
    L2_effect_size_Y, L2_p_value_Y = level_2(Y, A, B, permutations=permutations)

    # --- Level 3
    L3_mean_AX, L3_std_AX = level_3(X, A)
    L3_mean_BX, L3_std_BX = level_3(X, B)
    L3_mean_AY, L3_std_AY = level_3(Y, A)
    L3_mean_BY, L3_std_BY = level_3(Y, B)

    return {
```

```
        'L1_effect_size': L1_effect_size,
        'L1_p_value': L1_p_value,

        'L2_effect_size_X': L2_effect_size_X,
        'L2_p_value_X': L2_p_value_X,
        'L2_effect_size_Y': L2_effect_size_Y,
        'L2_p_value_Y': L2_p_value_Y,

        'L3_mean_AX': L3_mean_AX,
        'L3_std_AX': L3_std_AX,
        'L3_mean_BX': L3_mean_BX,
        'L3_std_BX': L3_std_BX,
        'L3_mean_AY': L3_mean_AY,
        'L3_std_AY': L3_std_AY,
        'L3_mean_BY': L3_mean_BY,
        'L3_std_BY': L3_std_BY,
    }

##################################################
# 4) Optional: Utility to fetch embeddings by word index
##################################################
def get_np_embeddings(
    target_words: list,
    vocab_dict: dict,
    embeddings: np.ndarray
) -> np.ndarray:
    """
    Given a list of words, a vocab->index dict, and the raw embedding matrix,
    returns an array of shape (len(target_words), embedding_dim).
    """
    return np.array([embeddings[vocab_dict[word]] for word in target_words])
```

[36]:
```
################################################################################
# Convert male, female, and the single set of adjectives to NumPy arrays
################################################################################

# We already have:
MALE_WORDS = ["man", "kerel", "jongen", "vader", "zoon", "vent", "gast",␣
 ↪"meneer", "opa", "oom"]
FEMALE_WORDS = ["vrouw", "dame", "meisje", "moeder", "dochter", "meid",␣
 ↪"mevrouw", "oma","tante"]

# Single set of adjectives (the big list of 2741 items after filtering)
# from "filtered_adjectives"
adjective_list = list(filtered_adjectives)

# Now, fetch vectors from your Word2Vec KeyedVectors (model_w2v)
```

```
male_vecs = np.array([w2v_model[w] for w in MALE_WORDS if w in w2v_model])
female_vecs = np.array([w2v_model[w] for w in FEMALE_WORDS if w in w2v_model])
adjective_vecs = np.array([w2v_model[w] for w in adjective_list if w in␣
↪w2v_model])

print("Shapes:")
print("male_vecs:", male_vecs.shape)
print("female_vecs:", female_vecs.shape)
print("adjective_vecs:", adjective_vecs.shape)

################################################################################
#  Use level_3(...) on each target group vs. your single attribute set
################################################################################

mean_male, std_male = level_3(male_vecs, adjective_vecs)
mean_female, std_female = level_3(female_vecs, adjective_vecs)

print("=== Level 3 with a single attribute set of adjectives ===")
print(f"Male-coded -> Adjectives: mean={mean_male:.3f}, std={std_male:.3f}")
print(f"Female-coded -> Adjectives: mean={mean_female:.3f}, std={std_female:.
↪3f}")

# After you've computed these:
# mean_male, std_male = level_3(male_vecs, adjective_vecs)
# mean_female, std_female = level_3(female_vecs, adjective_vecs)
```

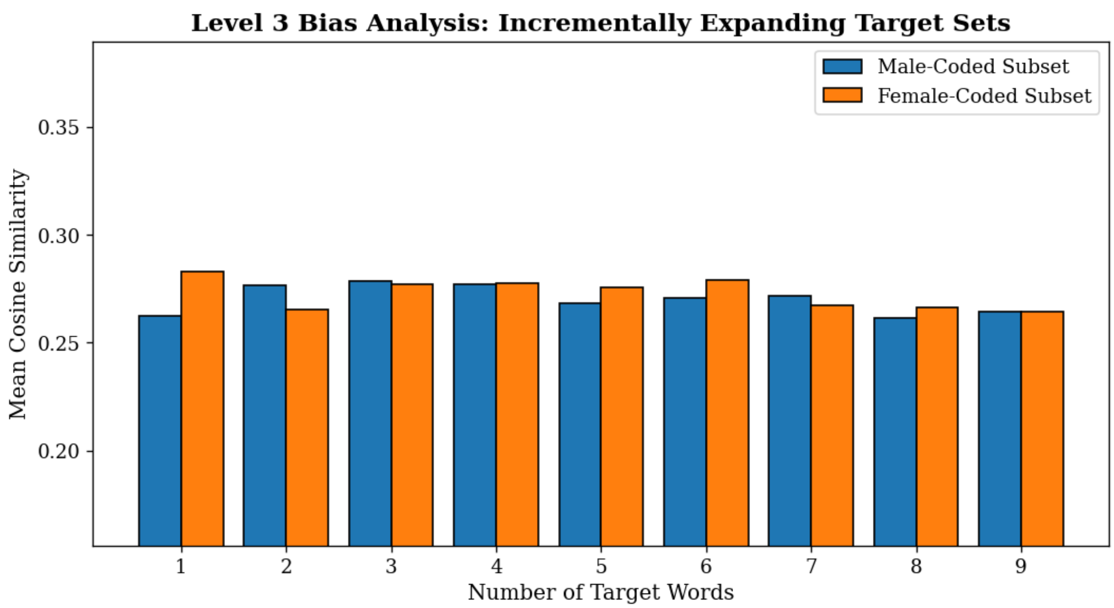
```
Shapes:
male_vecs: (10, 320)
female_vecs: (9, 320)
adjective_vecs: (2641, 320)
=== Level 3 with a single attribute set of adjectives ===
Male-coded -> Adjectives: mean=0.262, std=0.094
Female-coded -> Adjectives: mean=0.264, std=0.097
```

[37]:
```
###############################################################################
# 2) CONVERT THE MALE & FEMALE WORD LISTS INTO EMBEDDING MATRICES, PRESERVING␣
↪ORDER
###############################################################################
male_coded_vecs = []
for w in MALE_WORDS:
    if w in w2v_model:
        male_coded_vecs.append(w2v_model[w])
male_coded_vecs = np.array(male_coded_vecs)

female_coded_vecs = []
for w in FEMALE_WORDS:
    if w in w2v_model:
```

```
        female_coded_vecs.append(w2v_model[w])
female_coded_vecs = np.array(female_coded_vecs)

print(f"Male-coded full set has shape: {male_coded_vecs.shape}")
print(f"Female-coded full set has shape: {female_coded_vecs.shape}")
print(f"Adjective set has shape: {adjective_vecs.shape}")

###############################################################################
# 3) EXPAND FROM LEFT TO RIGHT:
#    - For subset size = 1, use only the first word in each list.
#    - For subset size = 2, use the first two words, etc.
###############################################################################
max_len = min(len(male_coded_vecs), len(female_coded_vecs))
subset_sizes = range(1, max_len + 1)

male_means, male_stds = [], []
female_means, female_stds = [], []

for size in subset_sizes:
    # Subset the first 'size' male-coded embeddings
    male_subset = male_coded_vecs[:size]
    mean_male, std_male = level_3(male_subset, adjective_vecs)
    male_means.append(mean_male)
    male_stds.append(std_male)

    # Subset the first 'size' female-coded embeddings
    female_subset = female_coded_vecs[:size]
    mean_female, std_female = level_3(female_subset, adjective_vecs)
    female_means.append(mean_female)
    female_stds.append(std_female)

male_means = np.array(male_means)
male_stds = np.array(male_stds)
female_means = np.array(female_means)
female_stds = np.array(female_stds)

###############################################################################
# 5) PLOT SIDE-BY-SIDE BARS WITH ERROR BARS (MEAN ± 1 STD), ZOOMED-IN Y-AXIS
###############################################################################
fig, ax = plt.subplots(figsize=(9, 5), dpi=120)

x_positions = np.arange(len(subset_sizes))
bar_width = 0.4

# Plot male-coded bars
ax.bar(
    x_positions - bar_width/2,
```

```
    male_means,
    width=bar_width,
    edgecolor='black',
    label="Male-Coded Subset",
    color="#1f77b4"
)

# Plot female-coded bars
ax.bar(
    x_positions + bar_width/2,
    female_means,
    width=bar_width,
    edgecolor='black',
    label="Female-Coded Subset",
    color="#ff7f0e"
)

# X-axis
ax.set_xticks(x_positions)
ax.set_xticklabels([str(s) for s in subset_sizes])
ax.set_xlabel("Number of Target Words", fontsize=12)

# Y-axis
ax.set_ylabel("Mean Cosine Similarity", fontsize=12)

# Optional: narrow the y-axis range to 'zoom in' if your data is in [0.22, 0.
↪28] etc.
all_means = np.concatenate([male_means, female_means])
all_stds = np.concatenate([male_stds, female_stds])
y_min = np.min(all_means - all_stds) - 0.01
y_max = np.max(all_means + all_stds) + 0.01
ax.set_ylim(y_min, y_max)

# Title & legend
ax.set_title("Level 3 Bias Analysis: Incrementally Expanding Target Sets",
             fontsize=14, fontweight='bold')
ax.axhline(0, color='gray', linestyle='--', linewidth=1)
ax.legend(fontsize=11)

plt.tight_layout()
plt.show()
```

```
Male-coded full set has shape: (10, 320)
Female-coded full set has shape: (9, 320)
Adjective set has shape: (2641, 320)
```



[38]:
```
## LEAVE ONE APPROACH (INSTEAD OF TRUNCATING I COULD LEAVE ONE OUT, TO SHOW␣
↪MARGINAL EFFECTS)
## COMPARE LLMS WHICH ARE FINED TUNED FOR CHAT (IF THEY ARE EVEN MORE BIASED?);␣
↪VERSUS PURE LANGUAGE MODELS.
    ### LANGUAGE MODEL (EFFECT OF RL FINE TUNING):
        llama-2-uncensored
        llama-2-chat
        PARAMETERS:
            temperature

    ### CHAT MODELS: {DISTILLED MODELS}
```

```
  Cell In[38], line 4
    llama-2-uncensored
    ^
IndentationError: unexpected indent
```