CSC2611 Lab: Word embedding and semantic change

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Link to the GitHub repository: https://github.com/JunXing2633/CSC2611

In [1]:
```
import pickle
import pandas as pd
import numpy as np
import statistics
from gensim.models import KeyedVectors
from scipy import stats,sparse
from scipy.spatial import distance
from nltk.util import ngrams
from nltk.corpus import brown
from collections import Counter
from tqdm import tqdm, trange
from tqdm.contrib import tzip
from decimal import Decimal
from sklearn.decomposition import PCA,TruncatedSVD
from sklearn.metrics.pairwise import cosine_similarity
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

```
c:\Users\royxj\miniconda3\envs\boc1\lib\site-packages\tqdm\auto.py:22: TqdmWarning: IProgress not found. Please update j
upyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

1 Synchronic word embedding [7 points]

In [2]:
```
# Step 1: Load data from exercise
datapath="./data/"
Pair = pickle.load(open(datapath+"P.pickle",'rb'))
human_jud = pickle.load(open(datapath+"S.pickle",'rb'))
rg65 = pickle.load(open(datapath+"rg65.pickle",'rb'))
w = pickle.load(open(datapath+"w.pickle",'rb'))  # 5000 most common English words based on unigram frequencies in the Br

df = pd.DataFrame(Pair, columns =['First_word', 'Second_word'])
df["human-judged similarities"] = human_jud

w.extend(rg65)
w_updated= list(set(w))
print(f"Updated W has {len(w_updated)} words.","\nThe common pairs of words used in all analyses are:\n",df)
```

```
Updated W has 5030 words.
The common pairs of words used in all analyses are:
     First_word Second_word  human-judged similarities
0         cord       smile                       0.02
1      rooster      voyage                       0.04
2         noon      string                       0.04
3        fruit     furnace                       0.05
4    autograph       shore                       0.06
..         ...         ...                        ...
59     cushion      pillow                       3.84
60    cemetery   graveyard                       3.88
61  automobile         car                       3.92
62      midday        noon                       3.94
63         gem       jewel                       3.94

[64 rows x 3 columns]
```

In [3]:
```
# Step 2: Construct word embedding models

def construct_models(W):
    '''
    Input: set of words W in a vocabulary

    output:
    1. constructed model M1, word-context vector model  by collecting bigram counts for words in W
    2. word to index and index to word dictionary
```

```
    3. Positive pointwise mutual information on M1, denoted as M1_plus
    4. M2_10, latent semantic model by applying principal components analysis to M1+ truncated dimentsion at 10
    5. M2_100, latent semantic model by applying principal components analysis to M1+ truncated dimentsion at 100
    6. M2_300, latent semantic model by applying principal components analysis to M1+ truncated dimentsion at 300
    6. pretrained word2vec

    '''

    if os.path.isfile(datapath+'M1.pickle'):

        M1 = pickle.load(open(datapath+"M1.pickle","rb"))
        word_2_index = pickle.load(open(datapath+"word_2_index.pickle","rb"))
        index_2_word = pickle.load(open(datapath+"index_2_word.pickle","rb"))
        M1_plus=pickle.load(open(datapath+"M1_plus.pickle","rb"))
    else:
        bigrams = Counter(ngrams([word.lower() for word in brown.words()], 2))
        M1 = sparse.lil_matrix((len(W), len(W)))
        word_2_index = {}
        index_2_word = {}

        for i ,w1 in enumerate(tqdm(W)):
            word_2_index[w1.lower()] = i
            index_2_word[i] = w1.lower()
            for j, w2 in enumerate(W):
                M1[i, j] = bigrams[(w1.lower(), w2.lower())]

        pickle.dump(M1, open(datapath+"M1.pickle","wb"))
        pickle.dump(word_2_index, open(datapath+"word_2_index.pickle","wb"))
        pickle.dump(index_2_word, open(datapath+"index_2_word.pickle","wb"))

        unigram = Counter(ngrams([word.lower() for word in brown.words()], 1))
        M1_plus = sparse.lil_matrix((len(w_updated), len(w_updated)))
        count_all_words = len(brown.words())
        nonzero_i, nonzero_j = M1.nonzero()
        for i, j in tzip(nonzero_i, nonzero_j):

            count1 = unigram[(index_2_word[i],)]
            count2 = unigram[(index_2_word[j],)]

            P1 =  count1 / count_all_words
            P2 =  count2 / count_all_words
            P1_2 = (M1[i, j]) / (M1.sum())
            M1_plus[i, j] = max(0, np.log( P1_2 / (P1 * P2)))

        pickle.dump(M1_plus, open(datapath+"M1_plus.pickle","wb"))

    print(f"M1 has a shape of {M1.shape}")
    print(f"M1_plus has a shape of {M1_plus.shape}")

    # PCA on sparse matrix
    M2_10 = TruncatedSVD(n_components=10, random_state=666).fit_transform(M1_plus)
    M2_100 = TruncatedSVD(n_components=100, random_state=666).fit_transform(M1_plus)
    M2_300 = TruncatedSVD(n_components=300, random_state=666).fit_transform(M1_plus)

    # model w2v googlenews pretarined negative 300
    w2v_pretrained = KeyedVectors.load_word2vec_format(datapath+'GoogleNews-vectors-negative300.bin.gz', binary=True)

    return M1,word_2_index,index_2_word,M1_plus, M2_10, M2_100, M2_300, w2v_pretrained

M1,word_2_index,index_2_word,M1_plus, M2_10, M2_100, M2_300, w2v_pretrained = construct_models(W=w_updated)
```

```
M1 has a shape of (5030, 5030)
M1_plus has a shape of (5030, 5030)
```

In [4]:

```
M1 = pickle.load(open(datapath+"M1.pickle","rb"))
word_2_index = pickle.load(open(datapath+"word_2_index.pickle","rb"))
index_2_word = pickle.load(open(datapath+"index_2_word.pickle","rb"))
M1_plus=pickle.load(open(datapath+"M1_plus.pickle","rb"))
df_M1 = pd.DataFrame.sparse.from_spmatrix(data = M1, index = word_2_index, columns = word_2_index)
df_M1
```

Out[4]:

	outside	seen	guilt	does	chemical	theme	window	enforcement	tangent	pope	...	voluntary	circles	could	distances
outside	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
seen	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
guilt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
does	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
chemical	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
decent	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
massachusetts	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
districts	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
access	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
interest	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0

5030 rows × 5030 columns

In [5]:

```
df_M1_plus = pd.DataFrame.sparse.from_spmatrix(data = M1_plus, index = word_2_index, columns = word_2_index)
df_M1_plus
```

Out[5]:

	outside	seen	guilt	does	chemical	theme	window	enforcement	tangent	pope	...	voluntary	circles	could	distances
outside	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
seen	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
guilt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
does	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
chemical	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
decent	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
massachusetts	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
districts	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
access	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0
interest	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0

5030 rows × 5030 columns

In [6]:

```
df_M2_10 = pd.DataFrame(data = M2_10, index = word_2_index)
df_M2_10
```

Out[6]:

	0	1	2	3	4	5	6	7	8	9
outside	3.874438	0.803934	-1.810792	1.149013	1.107951	-1.250064	1.902354	1.300893	0.040412	0.420604
seen	5.258244	-4.236508	-1.850233	4.818149	2.393508	-0.450808	1.018369	-1.258560	-0.745765	-0.493929
guilt	2.600411	-3.481472	-1.567675	-0.325477	-0.405340	0.439600	-0.484862	-0.013232	0.028681	0.082001
does	3.731283	-0.832924	2.082284	1.144864	5.268524	-1.670770	0.217214	1.548500	-0.553338	-0.527616
chemical	2.562249	2.162954	-1.556808	-1.365086	-0.554084	-0.660413	0.453128	-0.122109	-2.440434	-0.745986
...	...	...	...	...	...	...	...	...	...	...
decent	1.726032	0.837540	-0.853552	-0.146222	-0.183437	-0.134931	0.120748	-0.574950	-0.473440	-1.326989
massachusetts	1.642557	-0.947357	-0.414157	-0.505557	-0.406189	0.654516	-0.105402	0.420583	-0.059709	-0.228391
districts	2.078305	-2.370144	-0.806275	-0.499490	0.194369	0.288268	-0.378666	0.386752	-0.058738	-0.026791
access	1.695012	-1.763429	-1.256899	-0.184123	0.000690	0.074360	-0.242462	-0.360921	-0.747400	-0.055897
interest	4.764475	-4.286453	-1.918178	-1.681667	-0.971073	-0.225630	-1.245802	0.529753	-0.670169	0.078047

5030 rows × 10 columns

In [7]:

```python
# Calculate cosine distance between each pair of word embeddings
# Report the Pearson correlation between word2vec-based and human similarities
similar_M1 = []
similar_M1_plus = []
similar_M2_10 = []
similar_M2_100 = []
similar_M2_300 = []
similar_w2v=[]

for i,j in tzip([p[0] for p in Pair],[p[1] for p in Pair]):

  similar_M1.append(cosine_similarity(M1[word_2_index[i]].reshape(1, -1),M1[word_2_index[j]].reshape(1, -1))[0][0])
  similar_M1_plus.append(cosine_similarity(M1_plus[word_2_index[i]].reshape(1, -1),M1_plus[word_2_index[j]].reshape(1, -
  similar_M2_10.append(cosine_similarity(M2_10[word_2_index[i]].reshape(1, -1),M2_10[word_2_index[j]].reshape(1, -1))[0]
  similar_M2_100.append(cosine_similarity(M2_100[word_2_index[i]].reshape(1, -1),M2_100[word_2_index[j]].reshape(1, -1))
  similar_M2_300.append(cosine_similarity(M2_300[word_2_index[i]].reshape(1, -1),M2_300[word_2_index[j]].reshape(1, -1))
  similar_w2v.append(cosine_similarity(w2v_pretrained[i].reshape(1,-1),w2v_pretrained[j].reshape(1,-1))[0][0])

pearson_M1=stats.pearsonr(human_jud, similar_M1)
pearson_M1_plus=stats.pearsonr(human_jud, similar_M1_plus)
pearson_w2v=stats.pearsonr(human_jud, similar_w2v)
pearson_M2_10=stats.pearsonr(human_jud, similar_M2_10)
pearson_M2_100=stats.pearsonr(human_jud, similar_M2_100)
pearson_M2_300=stats.pearsonr(human_jud, similar_M2_300)

print(f"Pearson correlation between word2vec-based and human judgement are {round(pearson_w2v[0],3)} with p_value of {De
print(f"Pearson correlation between M1-based and human judgement are {round(pearson_M1[0],3)} with p_value of {Decimal(p
print(f"Pearson correlation between M1_plus-based and human judgement are {round(pearson_M1_plus[0],3)} with p_value of
print(f"Pearson correlation between M2_10-based and human judgement are {round(pearson_M2_10[0],3)} with p_value of {Dec
print(f"Pearson correlation between M2_100-based and human judgement are {round(pearson_M2_100[0],3)} with p_value of {D
print(f"Pearson correlation between M2_300-based and human judgement are {round(pearson_M2_300[0],3)} with p_value of {D
```

```
100%|██████████| 64/64 [00:00<00:00, 181.21it/s]
Pearson correlation between word2vec-based and human judgement are 0.769 with p_value of 1.148E-13
Pearson correlation between M1-based and human judgement are 0.324 with p_value of 8.986E-3
Pearson correlation between M1_plus-based and human judgement are 0.211 with p_value of 9.456E-2
Pearson correlation between M2_10-based and human judgement are 0.179 with p_value of 1.580E-1
Pearson correlation between M2_100-based and human judgement are 0.302 with p_value of 1.544E-2
Pearson correlation between M2_300-based and human judgement are 0.339 with p_value of 6.145E-3
```

Comment on this value in comparison to those from LSA and word-context vectors from analyses in the earlier exercise.

By comparing Pearson correlations between human adjustments and different models. We notice that word2vec generates much higher pearson correlation(0.769) than the other models.
We can conclude that embeddings from word2vec are more representative regards the words' meaning and association.

Also, as we increase dimensions of PCA, the word embedding yields better representation, so the higher Pearson correlation to the human judgement.

In [8]:
```
import requests
analogy_data = requests.get('http://www.fit.vutbr.cz/~imikolov/rnnlm/word-test.v1.txt')
```

In [9]:
```
file=analogy_data.text.split('\n')[1:]
Analogy_tests_dict = {}
for line in file:
  words_list = line.lower().split()
  if len(words_list)<1:
    pass
  elif words_list[0]==":":
    types_test = words_list[-1].strip()
    Analogy_tests_dict[types_test]=[]

  elif len(words_list) == 4 and (words_list[0] in w_updated) and (words_list[1] in w_updated) \
    and (words_list[2] in w_updated) and (words_list[3] in w_updated):
    Analogy_tests_dict[types_test].append((words_list[0], words_list[1], words_list[2], words_list[3]))
```

In [10]:
```
semantic_test = []
syntactic_test = []

for i in Analogy_tests_dict:
    if i.startswith("gram"):
        syntactic_test.extend(Analogy_tests_dict[i])
    else:
        semantic_test.extend(Analogy_tests_dict[i])
    print(i,":", len(Analogy_tests_dict[i]),"tests")

Analogy_tests_dict.pop("currency", None)

print("\nThe small test set I considered are the ones that all four words appear in W, which we used previously.")
print(f"Total semantic tests:  {len(semantic_test)}")
print(f"Total syntactic tests:  {len(syntactic_test)}")
```

```
capital-common-countries : 20 tests
capital-world : 6 tests
currency : 0 tests
city-in-state : 59 tests
family : 90 tests
gram1-adjective-to-adverb : 380 tests
gram2-opposite : 20 tests
gram3-comparative : 272 tests
gram4-superlative : 42 tests
gram5-present-participle : 272 tests
gram6-nationality-adjective : 87 tests
gram7-past-tense : 600 tests
gram8-plural : 306 tests
gram9-plural-verbs : 132 tests

The small test set I considered are the ones that all four words appear in W, which we used previously.
Total semantic tests:  175
Total syntactic tests:  2111
```

In [11]:
```
# prepare txt format that is consistent with "questions-words.txt" file available from the original word2vec.c distribut
# so that API evaluate word analogies can be used for analogy tests

with open(datapath+"semantic_tests.txt", "w") as f1:
    for ele in Analogy_tests_dict:
        if not ele.startswith("gram"):
            f1.write(f": {ele}\n")
            for words in Analogy_tests_dict[ele]:

                f1.write(f"{words[0]}\t")
                f1.write(f"{words[1]}\t")
                f1.write(f"{words[2]}\t")
                f1.write(f"{words[3]}\n")
f1.close()
with open(datapath+"syntactic_tests.txt", "w") as f2:
    for ele in Analogy_tests_dict:
        if ele.startswith("gram"):
            f2.write(f": {ele}\n")
            for words in Analogy_tests_dict[ele]:
                f2.write(f"{words[0]}\t")
                f2.write(f"{words[1]}\t")
                f2.write(f"{words[2]}\t")
                f2.write(f"{words[3]}\n")
f2.close()
```

```
lsa_M2_300 = KeyedVectors(vector_size=300)
lsa_M2_300.add_vectors(keys=list(word_2_index.keys()), weights=M2_300)

semantic_acc_w2v = w2v_pretrained.evaluate_word_analogies(datapath+'semantic_tests.txt')
syntactic_acc_w2v = w2v_pretrained.evaluate_word_analogies(datapath+'syntactic_tests.txt')
semantic_acc_lsa = lsa_M2_300.evaluate_word_analogies(datapath+'semantic_tests.txt')
syntactic_acc_lsa = lsa_M2_300.evaluate_word_analogies(datapath+'syntactic_tests.txt')

print(f"Word2vec yields a accuracy of {round(semantic_acc_w2v[0]*100,3)}% on the {len(semantic_test)} semantic analogy t
print(f"Word2vec yields a accuracy of {round(syntactic_acc_w2v[0]*100,3)}% on the {len(syntactic_test)} syntactic analog
print(f"LSA_M2_300 yields a accuracy of {round(semantic_acc_lsa[0]*100,3)}% on the {len(semantic_test)} semantic analogy
print(f"LSA_M2_300 yields a accuracy of {round(syntactic_acc_lsa[0]*100,3)}% on the {len(syntactic_test)} syntactic anal
```

```
Word2vec yields a accuracy of 88.0% on the 175 semantic analogy tests.
Word2vec yields a accuracy of 68.593% on the 2111 syntactic analogy tests.
LSA_M2_300 yields a accuracy of 8.571% on the 175 semantic analogy tests.
LSA_M2_300 yields a accuracy of 7.39% on the 2111 syntactic analogy tests.
```

Discussion:

As the results shown above, we can tell that word2vec outperforms LSA_M2_300 in both semantic and syntactic analogy tests. Even though the two embedding vector representation has the same dimension (300), but word2vec embeddings was trained on much larger dataset. Therefore, it embeddings are more representative of word meaning and association.

Suggest a way to improve the existing set of vector-based models in capturing word similarities in general, and provide justifications for your suggestion.

1. In general, we can try to use larger training dataset, larger language model, and increase the dimension of a vector representation. As a result, such embedding vector are more representative by its context, leads to better capture of the word similarities. However, it also means longer training time and more computational resources.

2. Second of all, outside the model, we can use engineering techniques such as "preprocess" and "postprocess". For example, we can do lemmatization/steamming to treat words with different morphology forms to same token. We can use black/white list to enforce rules that artificailly increase the word similarities. We can use Part of Speech tags so that word with multiple unrelated senses can be treated as different token. Therefore, the model as a whole, would be able to capture word similarities better.

2 Diachronic word embedding [8 points]

Step 1. Download the diachronic word2vec embeddings from the course syllabus page. These embeddings capture historical usage of a small subset of English words over the past century

In [12]:
```
diachronic_data = pickle.load(open(datapath+"data.pkl","rb"))
diachronic_words=diachronic_data['w']
diachronic_decades=diachronic_data['d']
diachronic_vectors=diachronic_data['E']
print(len(set(diachronic_words))) #confirm all words are unique
print(diachronic_decades)
```

```
2000
[1900, 1910, 1920, 1930, 1940, 1950, 1960, 1970, 1980, 1990]
```

In [13]:
```
from sklearn.neighbors import NearestNeighbors

def get_nearest_neighbor(word,year,k):
    # This is a helper function which gets k nearest neighbor words
    if word not in diachronic_words or year not in diachronic_decades:
        return []

    word_idx = diachronic_words.index(word)
    yr_idx = diachronic_decades.index(year)

    matrix_year = []
    for i in range(len(diachronic_vectors)):
        matrix_year.append(diachronic_vectors[i][yr_idx])
    matrix_year = np.array(matrix_year)

    knn_temp = NearestNeighbors(n_neighbors=k)
    knn_temp.fit(matrix_year)

    vector_temp = diachronic_vectors[word_idx][yr_idx].reshape(1, -1)
```

```
    neighbor_idx = knn_temp.kneighbors(vector_temp,k,return_distance=False)

    ret = [diachronic_words[i] for i in list(neighbor_idx)[0]]
    ret.remove(word)
    return ret

def cal_jaccard(list_a,list_b):
    # This is a helper function which calculates jaccard distances
    intersect = set(list_a).intersection(list_b)
    union = len(list_a)+len(list_b)-len(intersect)
    ret = 1-len(intersect)/union
    return ret
```

Step 2. Propose three different methods for measuring degree of semantic change for individual words and report the top 20 most and least changing words in table(s) from each measure.

In [14]:
```
def methods_semantic_change(word,method):

    '''
    This is the main function
    input:
    1. word: a word (string) for which we need to quantify the semantic change between 1900 and 1990
    2. method: int to represent which method to use
            method 1: consider the change(cosine-distance) of the two end points, Larger the cosine distance, larger the
            mehotd 2: cosider the average of the changes(cosine-distance) of over 10 years. Larger the average, larger t
            method 3: cosider the standard deviation of the changes(cosine-distance) of over 10 years. Larger the std, l
            method 4: This is the proposed procedure to evaluate accuracy of method 1-3, It considers jaccard distance b
    output:
    semantic change as defined

    '''
    idx = diachronic_words.index(word)
    embed1 = diachronic_vectors[idx][0]
    embed2 = diachronic_vectors[idx][-1]
    if method==1:
        return distance.cosine(embed1,embed2)
    elif method==2:
        temp=[]
        for i in range(len(diachronic_vectors[idx])-1):
            temp.append(distance.cosine(diachronic_vectors[idx][i],diachronic_vectors[idx][i+1]))
        return sum(temp)/len(temp)
    elif method==3:
        temp=[]
        for i in range(len(diachronic_vectors[idx])-1):
            temp.append(distance.cosine(diachronic_vectors[idx][i],diachronic_vectors[idx][i+1]))
        return statistics.stdev(temp)

    elif method==4:
        list_a = get_nearest_neighbor(word,year=1900,k=26)
        list_b = get_nearest_neighbor(word,year=1990,k=26)

        return cal_jaccard(list_a,list_b)
```

In [15]:
```
semantic_change_method1={}
semantic_change_method2={}
semantic_change_method3={}
for word in diachronic_words:
    semantic_change_method1[word]=methods_semantic_change(word,method=1)
    semantic_change_method2[word]=methods_semantic_change(word,method=2)
    semantic_change_method3[word]=methods_semantic_change(word,method=3)

top20_method1 = sorted(semantic_change_method1, key=semantic_change_method1.get, reverse=True)[:20]
bottom20_method1 = sorted(semantic_change_method1, key=semantic_change_method1.get, reverse=False)[:20]
top20_method2 = sorted(semantic_change_method2, key=semantic_change_method2.get, reverse=True)[:20]
bottom20_method2 = sorted(semantic_change_method2, key=semantic_change_method2.get, reverse=False)[:20]
top20_method3 = sorted(semantic_change_method3, key=semantic_change_method3.get, reverse=True)[:20]
bottom20_method3 = sorted(semantic_change_method3, key=semantic_change_method3.get, reverse=False)[:20]
```

In [16]:
```
df_most_changing=pd.DataFrame({"Method_1":top20_method1,"Method_2":top20_method2,"Method_3":top20_method3})
print("The top 20 most changing words by each method are:")
df_most_changing.transpose()
```

```
The top 20 most changing words by each method are:
```

Out[16]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
Method_1	programs	objectives	computer	radio	sector	goals	approach	van	shri	media	impact	perspective	patterns
Method_2	harper	jones	sector	berkeley	wiley	baltimore	martin	princeton	wilson	adams	therapy	johnson	goals
Method_3	goals	objectives	computer	programs	sector	evaluation	input	techniques	therapy	mcgraw	shri	procedures	ml

In [17]:

```python
df_least_changing=pd.DataFrame({"Method_1":bottom20_method1,"Method_2":bottom20_method2,"Method_3":bottom20_method3})
print("The bottom 20 least changing words by each method are:")
df_least_changing.transpose()
```

```
The bottom 20 least changing words by each method are:
```

Out[17]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
Method_1	techniques	skills	mcgraw	ml	april	june	november	february	years	october	increase	january	century
Method_2	shri	april	miles	november	september	january	december	february	university	vessels	trees	cent	solution
Method_3	november	increase	reply	article	card	root	calcium	rome	jurisdiction	situation	president	act	pair

Measure the intercorrelations (of semantic change in all words, given the embeddings from Step 1) among the three methods you have proposed and summarize the Pearson correlations in a 3-by-3 table

In [18]:

```python
method1_distances = []
method2_distances = []
method3_distances = []
for word in diachronic_words:
    method1_distances.append(semantic_change_method1[word])
    method2_distances.append(semantic_change_method2[word])
    method3_distances.append(semantic_change_method3[word])

pearsonr_method1_2=round((stats.pearsonr(method1_distances, method2_distances))[0],3)
pearsonr_method2_3=round((stats.pearsonr(method2_distances, method3_distances))[0],3)
pearsonr_method3_1=round((stats.pearsonr(method3_distances, method1_distances))[0],3)
```

In [36]:

```python
print(f"The numpy cross-correlation between results from Method 1 and Method 2 is {round(np.correlate(method1_distances,
print(f"The numpy cross-correlation between results from Method 2 and Method 3 is {round(np.correlate(method2_distances,
print(f"The numpy cross-correlation between results from Method 1 and Method 3 is {round(np.correlate(method3_distances,
```

```
The numpy cross-correlation between results from Method 1 and Method 2 is 245.228
The numpy cross-correlation between results from Method 2 and Method 3 is 12.551
The numpy cross-correlation between results from Method 1 and Method 3 is 25.775
```

In [20]:

```python
df_method_corr=pd.DataFrame.from_records([[1,pearsonr_method1_2,pearsonr_method3_1],\
    [pearsonr_method1_2,1,pearsonr_method2_3],\
        [pearsonr_method3_1,pearsonr_method2_3,1]],columns = ["Method_1","Method_2","Method_3"])
df_method_corr["_"]=["Method_1","Method_2","Method_3"]
df_method_corr.set_index(["_"], inplace = True)
print("Pearson correlations of the semantic changes by 3 methods are summarized as following table:\n")
df_method_corr
```

```
Pearson correlations of the semantic changes by 3 methods are summarized as following table:
```

Out[20]:

_	Method_1	Method_2	Method_3
Method_1	1.000	0.64	0.367
Method_2	0.640	1.00	0.360
Method_3	0.367	0.36	1.000

- Method 1 is based on the change(cosine-distance) of the two end points.
- Method 2 is based the average of the changes(cosine-distance) of over 10 years.
- Method 3 is based on the standard deviation of the changes(cosine-distance) of over 10 years.

Step 3. Propose and justify a procedure for evaluating the accuracy of the methods you have proposed in Step 2, and then evaluate the three methods following this proposed procedure and report Pearson correlations or relevant test statistics.

Proposed Evaluation:
The proposed procedure has two parts:
Part 1: establish a new method to quantify true semantic change

1. get set of k nearest neighbor in first year
2. get set of k nearest neighbor in final year
3. calculate jaccard distance between the two sets, the greater difference, the larger the semantic change.

Part 2:

1. compare jaccard similarity between sets of top 20 and bottom 20 from 3 methods and that from proposed method
2. calculate pearson correlation between all distances from 3 methods and that from proposed method

The rationale is that if the meaning of a word does not change, its neighbor should be approximately the same. Notice that different values of k have been experimented. Different k results in different top20 and bottom 20 changing words, but it does not change the evaluation of 3 methods.

In [21]:
```
semantic_change_proposed={}
for word in diachronic_words:
    semantic_change_proposed[word]=methods_semantic_change(word,method=4)

top20_proposed = sorted(semantic_change_proposed, key=semantic_change_proposed.get, reverse=True)[:20]
bottom20_proposed = sorted(semantic_change_proposed, key=semantic_change_proposed.get, reverse=False)[:20]
```

In [22]:
```
df_most_changing=pd.DataFrame({"Method_1":top20_method1,"Method_2":top20_method2,"Method_3":top20_method3,"Proposed":top
print("The top 20 most changing words by each method are:")
df_most_changing.transpose()
```

```
The top 20 most changing words by each method are:
```

Out[22]:

	0	1	2	3	4	5	6	7	8	9	10	11	1
Method_1	programs	objectives	computer	radio	sector	goals	approach	van	shri	media	impact	perspective	patter
Method_2	harper	jones	sector	berkeley	wiley	baltimore	martin	princeton	wilson	adams	therapy	johnson	goa
Method_3	goals	objectives	computer	programs	sector	evaluation	input	techniques	therapy	mcgraw	shri	procedures	r
Proposed	impact	sector	radio	mcgraw	ml	approach	computer	techniques	signal	skills	assessment	perspective	syste

In [23]:
```
jac_top20_method1_p=round(1-cal_jaccard(top20_method1,top20_proposed),3)
jac_top20_method2_p=round(1-cal_jaccard(top20_method2,top20_proposed),3)
jac_top20_method3_p=round(1-cal_jaccard(top20_method3,top20_proposed),3)
print(f"Jaccard Similaritity Between Top20 by Method 1 and that from Proposed is: {jac_top20_method1_p}")
print(f"Jaccard Similaritity Between Top20 by Method 2 and that from Proposed is: {jac_top20_method2_p}")
print(f"Jaccard Similaritity Between Top20 by Method 3 and that from Proposed is: {jac_top20_method3_p}")
```

```
Jaccard Similaritity Between Top20 by Method 1 and that from Proposed is: 0.333
Jaccard Similaritity Between Top20 by Method 2 and that from Proposed is: 0.026
Jaccard Similaritity Between Top20 by Method 3 and that from Proposed is: 0.29
```

In [24]:
```
df_least_changing=pd.DataFrame({"Method_1":bottom20_method1,"Method_2":bottom20_method2,"Method_3":bottom20_method3,"Pro
print("The bottom 20 least changing words by each method are:")
df_least_changing.transpose()
```

```
The bottom 20 least changing words by each method are:
```

Out[24]:

	0	1	2	3	4	5	6	7	8	9	10	11	1
Method_1	techniques	skills	mcgraw	ml	april	june	november	february	years	october	increase	january	centur
Method_2	shri	april	miles	november	september	january	december	february	university	vessels	trees	cent	solutio
Method_3	november	increase	reply	article	card	root	calcium	rome	jurisdiction	situation	president	act	pa
Proposed	morning	illinois	iowa	december	summer	wisconsin	kitchen	missouri	indiana	minnesota	autumn	days	sout

In [25]:
```
jac_bottom20_method1_p=round(1-cal_jaccard(bottom20_method1,bottom20_proposed),3)
jac_bottom20_method2_p=round(1-cal_jaccard(bottom20_method2,bottom20_proposed),3)
```

```
jac_bottom20_method3_p=round(1-cal_jaccard(bottom20_method3,bottom20_proposed),3)
print(f"Jaccard Similaritity Between Bottom20 by Method 1 and that from Proposed is: {jac_bottom20_method1_p}")
print(f"Jaccard Similaritity Between Bottom20 by Method 2 and that from Proposed is: {jac_bottom20_method2_p}")
print(f"Jaccard Similaritity Between Bottom20 by Method 3 and that from Proposed is: {jac_bottom20_method3_p}")
```

```
Jaccard Similaritity Between Bottom20 by Method 1 and that from Proposed is: 0.111
Jaccard Similaritity Between Bottom20 by Method 2 and that from Proposed is: 0.111
Jaccard Similaritity Between Bottom20 by Method 3 and that from Proposed is: 0.026
```

In [26]:

```
proposed_distances = []
for word in diachronic_words:
    proposed_distances.append(semantic_change_proposed[word])

pearsonr_method1_p=round((stats.pearsonr(method1_distances, proposed_distances))[0],3)
pearsonr_method2_p=round((stats.pearsonr(method2_distances, proposed_distances))[0],3)
pearsonr_method3_p=round((stats.pearsonr(method3_distances, proposed_distances))[0],3)

df_method_corr=pd.DataFrame.from_records([[1,pearsonr_method1_2,pearsonr_method3_1,pearsonr_method1_p],\
    [pearsonr_method1_2,1,pearsonr_method2_3,pearsonr_method2_p],\
        [pearsonr_method3_1,pearsonr_method2_3,1,pearsonr_method3_p],\
            [pearsonr_method1_p,pearsonr_method2_p,pearsonr_method3_p,1]],columns = ["Method_1","Method_2","Method_3","P
df_method_corr["_"]=["Method_1","Method_2","Method_3","Proposed"]
df_method_corr.set_index(["_"], inplace = True)
print("Pearson correlations of the semantic changes by 3 methods and proposed evaluation are summarized as following tab
df_method_corr
```

```
Pearson correlations of the semantic changes by 3 methods and proposed evaluation are summarized as following table:
```

Out[26]:

_	Method_1	Method_2	Method_3	Proposed
Method_1	1.000	0.640	0.367	0.416
Method_2	0.640	1.000	0.360	0.164
Method_3	0.367	0.360	1.000	0.237
Proposed	0.416	0.164	0.237	1.000

Based on Jaccard Similaritity and Pearson Correlations with proposed evaluation, Method_1 outperforms the other two methods.

Step 4. Extract the top 3 changing words using the best method from Steps 2 and 3. Propose and implement a simple way of detecting the point(s) of semantic change in each word based on its diachronic embedding time course—visualize the time course and the detected change point(s)

In [27]:

```
top1,top2,top3=top20_proposed[:3]
print(f"Top 3 chaning words using best method are {top1},{top2},and {top3}.")
```

```
Top 3 chaning words using best method are impact,sector,and radio.
```

The strategy of detecting changing points is to plot time series of semantic change using both cosine distance of two embeddings and jaccard distance of two sets of nearest neighbors.

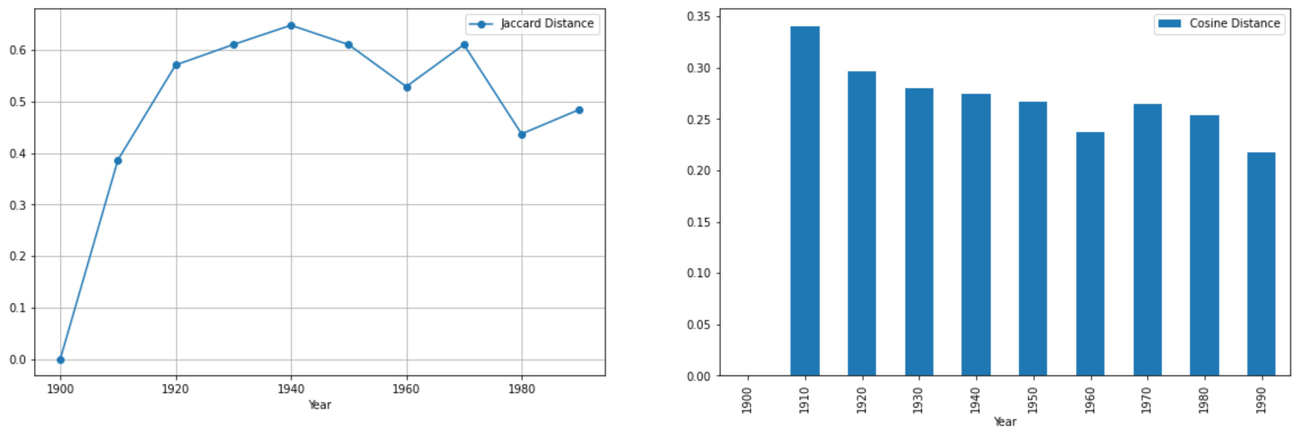
In [28]:

```
    def plot_semantic_change_series(word):
        # This is helper function which plots the semantic change over 10 years
        idx = diachronic_words.index(word)
        temp_method1=[0]
        temp_method4=[0]
        for i in range(len(diachronic_vectors[idx])-1):
            temp_method1.append(distance.cosine(diachronic_vectors[idx][i],diachronic_vectors[idx][i+1]))
            la=get_nearest_neighbor(word,year=diachronic_decades[i],k=26)
            lb=get_nearest_neighbor(word,year=diachronic_decades[i+1],k=26)
            temp_method4.append(cal_jaccard(la,lb))

        df_result = pd.DataFrame({"Year":diachronic_decades,"Cosine Distance":temp_method1,"Jaccard Distance":temp_metho
        #df_result.set_index("Year",inplace=True)
        figure, axes = plt.subplots(1, 2)
        figure.set_figheight(6)
        figure.set_figwidth(20)
        figure.suptitle(f"Semantic Change of \"{word}\" from Year {diachronic_decades[0]} to {diachronic_decades[-1]}", 

        df_result[['Year', 'Jaccard Distance']].plot(x='Year', grid=True, marker='o',ax=axes[0])
        df_result[['Year', 'Cosine Distance']].plot(x='Year', kind='bar',ax=axes[1])
```

```
        plt.show()
```

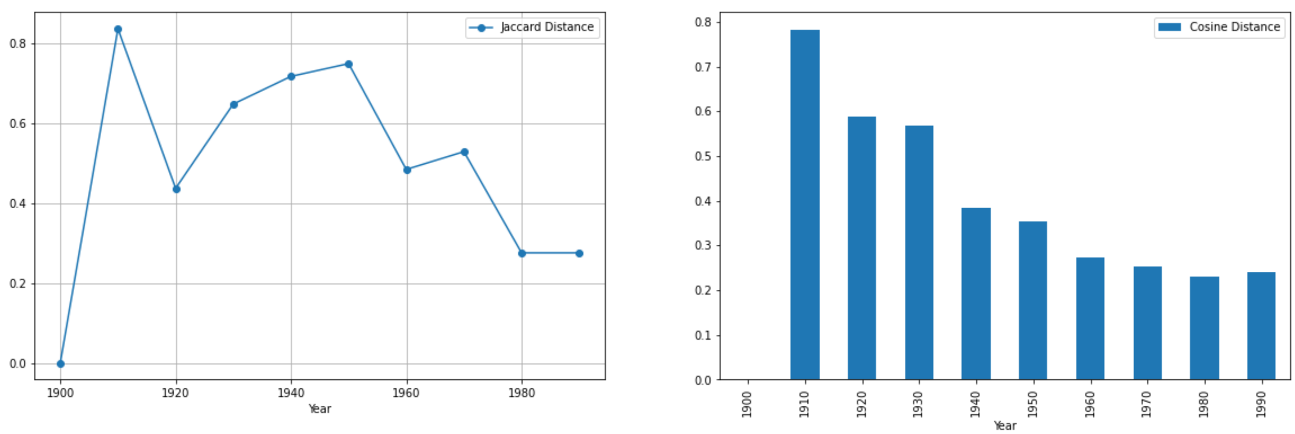
In [29]:
```
plot_semantic_change_series(word=top1)
```

Semantic Change of "impact" from Year 1900 to 1990



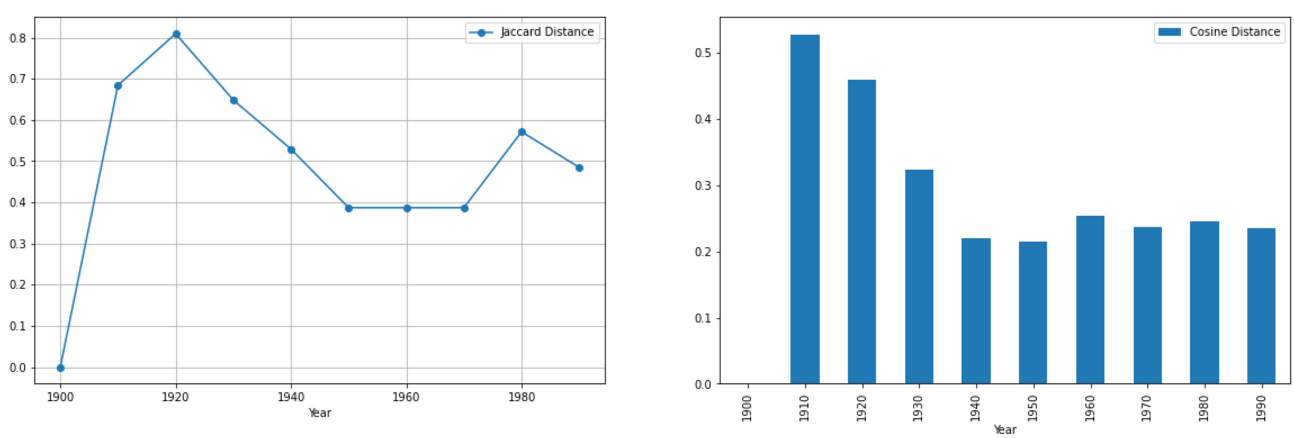
In [30]:
```
plot_semantic_change_series(word=top2)
```

Semantic Change of "sector" from Year 1900 to 1990



In [31]:
```
plot_semantic_change_series(word=top3)
```

Semantic Change of "radio" from Year 1900 to 1990



Based on the plots above, it seems that all top 3 chaning words have their change points in the first year. Let us confirm by comparing the chaning neighbors.

In [32]:
```
def confirm_neighbors_change(word):
    a=get_nearest_neighbor(word=word,year=1900,k=26)
    b=get_nearest_neighbor(word=word,year=1910,k=26)
    print(f"The nearest 25 neighbor for \'{word}\' in year 1900 are :\n{a}")
```

```python
    print(f"The nearest 25 neighbor for \'{word}\' in year 1910 are :\n{b}")
    ret = round(len(set(a).intersection(b))/26*100,1)
    print(f"The overlap portion is {ret}%")
```

In [33]:
```python
confirm_neighbors_change(word=top1)
```

```
The nearest 25 neighbor for 'impact' in year 1900 are :
['mcgraw', 'ml', 'techniques', 'skills', 'velocity', 'shock', 'radiation', 'waves', 'particle', 'particles', 'ions', 'mo
lecules', 'electrons', 'pressure', 'intensity', 'rays', 'wave', 'action', 'contact', 'stress', 'motion', 'beam', 'forc
e', 'components', 'wind']
The nearest 25 neighbor for 'impact' in year 1910 are :
['techniques', 'shri', 'ml', 'computer', 'skills', 'velocity', 'shock', 'waves', 'electrons', 'pressure', 'particles',
'molecules', 'rays', 'particle', 'ions', 'wind', 'blow', 'wave', 'force', 'radiation', 'atoms', 'contact', 'component',
'stress', 'effects']
The overlap portion is 73.1%
```

In [34]:
```python
confirm_neighbors_change(word=top2)
```

```
The nearest 25 neighbor for 'sector' in year 1900 are :
['techniques', 'skills', 'ml', 'mcgraw', 'diameter', 'radius', 'area', 'angle', 'circle', 'center', 'input', 'c', 'axi
s', 'areas', 'h', 'size', 'sphere', 'k', 'base', 'management', 'r', 'p', 'cylinder', 'fig', 'n']
The nearest 25 neighbor for 'sector' in year 1910 are :
['shri', 'ml', 'computer', 'skills', 'techniques', 'front', 'corps', 'centre', 'area', 'divisions', 'portion', 'divisio
n', 'line', 'circle', 'radius', 'wing', 'center', 'border', 'troops', 'zone', 'north', 'commander', 'command', 'curve',
'south']
The overlap portion is 26.9%
```

In [35]:
```python
confirm_neighbors_change(word=top3)
```

```
The nearest 25 neighbor for 'radio' in year 1900 are :
['techniques', 'skills', 'ml', 'mcgraw', 'electrons', 'substances', 'interaction', 'properties', 'activity', 'radiatio
n', 'fluid', 'electron', 'nerve', 'atoms', 'substance', 'tissues', 'processes', 'molecules', 'correlation', 'atom', 'equ
ilibrium', 'reactions', 'elements', 'bodies', 'absorption']
The nearest 25 neighbor for 'radio' in year 1910 are :
['computer', 'skills', 'techniques', 'shri', 'ml', 'substances', 'compounds', 'properties', 'elements', 'phenomena', 'ac
tivity', 'telephone', 'interaction', 'processes', 'electricity', 'atoms', 'energy', 'engineers', 'particles', 'bodies',
'frequency', 'reactions', 'metals', 'institute', 'structures']
The overlap portion is 46.2%
```