# NLP course Assignment 1: Distributional Similarity

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## Dense vectors (word2vec based similarities)

In this section of the assignment, we explored word-similarities induced by a word-embedding algorithm. We used the ‘*word2vec-google-news-300’* pre-trained vectors, from the *gensim* python package.

we explored word similarities in several manners as detailed below:

### Generating lists of the most similar words

We chose 5 words out of the vocabulary, and for each of them, we generated a list of the 20 most similar words according to word2vec algorithm. Later, on the second part of the assignment we will analyze these lists in comparison to ChatGPT output.

**Our 5 words are: espresso, game, spy, Computer, run.**

Results:

|  |  |
| --- | --- |
| **word** | **20 most similar words (decreasing order)** |
| espresso | cappuccino, mocha, coffee, latte, caramel\_macchiato, ristretto, espressos, macchiato, chai\_latte, espresso\_cappuccino, caramel\_latte, vanilla\_latte, brewed\_coffee, iced\_coffee, nonfat\_latte, expresso, espresso\_latte, coffees, mocha\_latte, Lavazza\_coffee |
| game | games, play, match, matchup, agame, ballgame, thegame, opener, matches, tournament, playing, league, Game, scrimmages, fourgame, scrimmage, postseason, playoffs, gme, season |
| spy | spies, spying, espionage, spymaster, CIA, Spy, MI6, spymasters, intelligence, CIA\_operative, eavesdropping, covert, persecute\_dissidents, counterspy, counterintelligence, supersecret, counterspies, KGB, honeytrap, superspy |
| Computer | Computers, computer, Computing, Enterprises\_GoGrid\_Gomez, computers, Electronics, Genuitec\_Gizmox\_Glassbox\_Global, COMPUTER, Modules\_COMs, Information\_Technology, Microcomputer, Applied\_Computing, Lab\_International\_Concentsus, Marvell\_Plug, Microcomputers, Digital\_Forensics, PC, Malicious\_Attacks, Software, Laptops |
| run | runs, running, drive, ran, scamper, tworun\_double, go, twoout, walk, Mark\_Grudzielanek\_singled, Batterymate\_Miguel\_Olivo, homerun, threerun, Collin\_Salzenstein, basesloaded, fielder's\_choice\_grounder, Peter\_Bourjos\_tripled, Casey\_Kalenkosky, Scutaro\_singled, clubbed\_solo\_homer |

### Polysemous Words

Polysemous words are words that have several meanings.  
we asked to find three polysemous such that the top-10 neighbours of each word reflect both word meanings (Group 1), and three polysemous words such that the top-10 neighbours of each word reflect only a single meaning (Group 2).  
we actually found relatively a lot of polysemous words but most of them were belong to group 2. We tried to think about attributes that associate word to group 1 like the sense frequency (maybe if one sense is significantly more frequent, the word vectors might be biased towards that dominant sense) or sense context (for example ‘bank’ represent two meanings but these are both places, in contrast to bass that reflects completely different meanings) but still, most of the words were belong to group 2. So, at the end it was somewhat trial and error.  
in our opinion, the sense frequency (mention above) is reasonable possible explanation for why the second group words neighbours reflect only one sense.   
In addition (and from here on these are just assumptions because we don’t know the training settings of the model), both training data and training settings have an influence on the embedding. For example, some settings would prefer morphologically similar words (like plurals, cat->cats) and other settings would consider semantically relevant words (like cat->dog). Different settings\algorithms can also differ in sensitivity to rare and frequent words and that connect to our first explanation.

**Group 1**

|  |  |  |
| --- | --- | --- |
| **word** | **possible senses** | **top-10 neighbours** |
| mole | small burrowing mammal, a common type of skin growth, spy, unit in chemistry | moles, pollo\_en, freckle, cancerous\_mole, birthmark, unibrow, spies, codenamed\_Stakeknife, nodule, pube |
| bass | type of fish, low-pitched musical instrument, low voice | crappie, largemouth, largemouths, largemouth\_bass, striper, stripers, smallmouth, Spotted\_bass, acoustic\_bass, upright\_bass |
| fall | season (also known as autumn), to drop or descend | falling, falls, drop, tumble, rise, plummet, fell, spring, Fall, sag |

Reflected sense are represented by colors

**Group 2**

|  |  |  |
| --- | --- | --- |
| **word** | **possible senses** | **top-10 neighbours** |
| rock | A relatively hard naturally occurring mineral material, music genre | rock\_n\_roll, rockers, punk\_emo, punk\_rock, alt\_rock, station\_WHJY\_FM, rocks, indie\_rock, star\_Gustavo\_Cerati, rock'n'roll |
| bar | drinking establishment, a straight piece (as of wood or metal) that is longer than it is wide (beam\rod) | Bar, bars, tavern, pub, nightspot, nightclub, Pub, bartender, restaurant, Lounge |
| plant | botanical organism (seed), factory | plants, Plant, factory, paperboard\_mill, containerboard\_mill, factories, megawatt\_MW\_biomass, refinery, Plants, mill |

Reflected sense are represented by colors

### Synonyms and Antonyms

We asked to find a triplet of words (w1, w2, w3) such that all the following conditions hold:

1. w1 and w2 are synonyms or almost synonyms.
2. w1 and w3 are antonyms.
3. sim(w1, w2) < sim(w1, w3)

**our words that meet all the conditions are: love, like, hate (w1, w2, w3 respectively)**

This behavior in which the antonyms are more similar than the synonyms can be explained by that in word embeddings, words that are often used in similar contexts are closer. In our example, "love" and "hate" only appear in the context of "feelings" while "like" can appear in context of "similarity" as well.

### The Effect of Different Corpora

In this part we compared two models based on two sources Wikipedia and twitter.

We asked to find 5 words whose top 10 neighbors based on the Wikipedia corpus are very similar to their top 10 neighbors based on the twitter corpus. And vice versa, 5 words whose top 10 neighbors based on the news corpus are substantially different from the top 10 neighbors based on the twitter corpus.our strategy to find those words was thinking about words that in the “twitter world” have different meanings. As we mentioned before, the similarities between words depend on if they appear in the same context so we search for words that in twitter will be in different context.

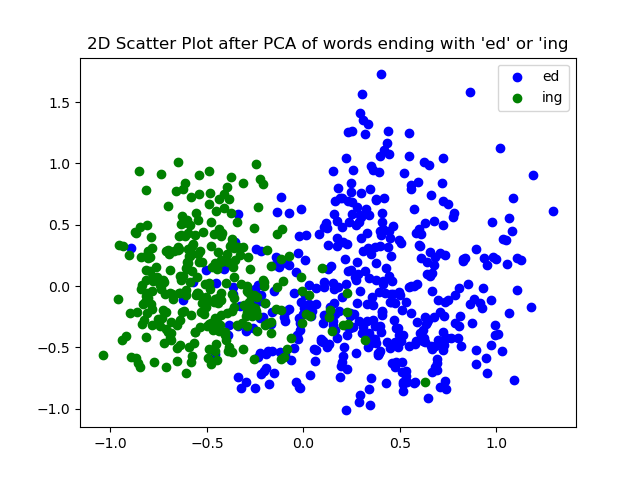
**Cross corpus similarity**

|  |  |  |
| --- | --- | --- |
| **Word** | **Wikipedia top-10 neighbours** | **Twitter top-10 neighbours** |
| yellow | red, pink, purple, blue, green, bright, colored, orange, black, colour | blue, purple, red, green, pink, white, orange, black, colored, bright |
| morning | afternoon, evening, friday, monday, thursday, night, tuesday, sunday, saturday, wednesday | afternoon, night, good, sunday, day, evening, monday, today, early, mornin |
| dog | dogs, cat, pet, puppy, horse, animal, cats, wolf, hound, pets | dogs, cat, puppy, pet, cats, horse, animal, kitten, little, kid |
| car | cars, vehicle, driver, truck, driving, vehicles, motorcycle, parked, drivers, bus | truck, cars, driving, drive, front, vehicle, bus, bike, cause, house |
| coffee | tea, cocoa, beans, espresso, drinks, drink, beer, wine, starbucks, sugar | tea, starbucks, coffe, beer, drink, iced, breakfast, milk, wine, latte |

**Cross corpus difference**

|  |  |  |  |
| --- | --- | --- | --- |
| **Word** | **Wikipedia top-10 neighbours** | **Twitter top-10 neighbours** | **difference description** |
| umbrella | organisation, organization, organisations, organizations, groups, alliance, grouping, group, non-governmental, non-profit | umbrellas, coat, rain, jacket, raining, parasol, bag, rains, outside, backpack | Wikipedia meaning: association of institutions who work together  Twitter meaning: protection against the rain |
| troll | trolls, monster, witch, doll, ape, mermaid, tentacled, sorcerer, monsters, medusa | trolls, trolling, noob, hacker, fail, bully, pervert, nerd, hack, trolled | Wikipedia meaning: a mythical creature  Twitter meaning: to antagonize others online |
| profile | recent, prominent, profiles, high-profile, attention, publicized, celebrity, political, similar, focus | page, picture, check, website, view, account, pic, click, add, visit | Wikipedia meaning: level of public exposure twitter meaning: user profile in social media |
| mute | deaf, blind, helpless, silent, storks, bedridden, ignorant, swans, cornetts, motionless | refresh, button, disable, delete, deaf, screen, remote, pause, block, muting | Wikipedia meaning: person who have speech disorder  Twitter meaning: function to eliminate sound in apps |
| gaming | gambling, casino, casinos, entertainment, poker, interactive, gamers, bingo, online, multiplayer | xbox, console, playstation, gamer, gamers, videogames, tech, desktop, controller, nintendo | Wikipedia meaning: playing gambling  Twitter meaning:  playing video games |

### Plotting words in 2D - Dimensionality Reduction

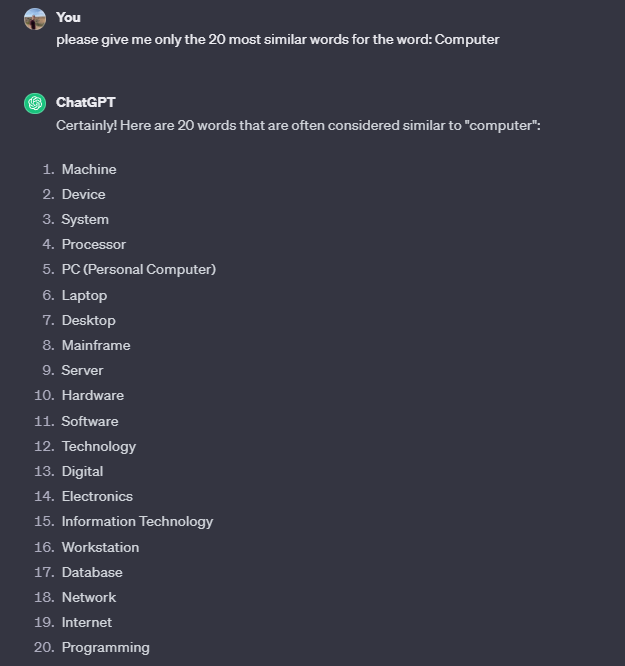
In this part we took the first 5000 words in the google model vocabulary, keeping just the words ending with “ed” and “ing” (verbs) and implemented a dimensionality reduction using PCA to transform the 300-dim matrix to 2-d so we can plot it:

points that correspond to words that end with “ed” are colored in blue and points that correspond to words that end with “ing” in green.

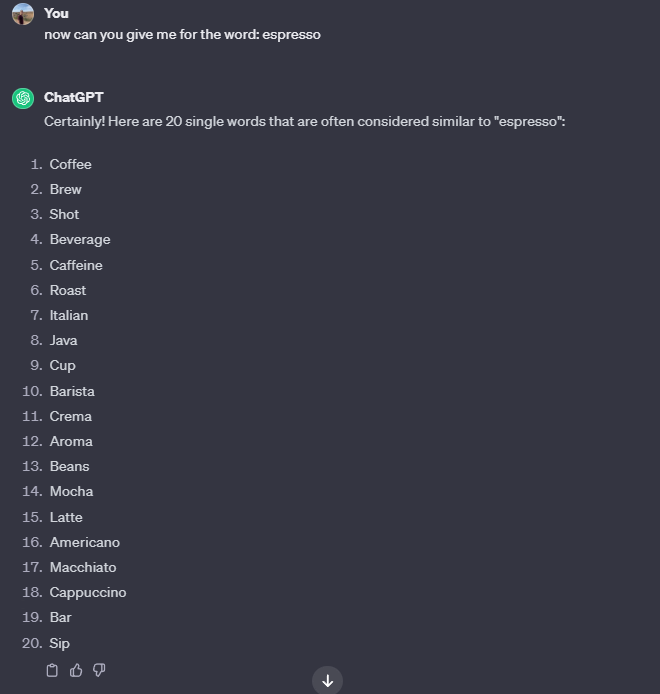
As we can see the two classes are slightly separate, indicates that the model might distinguished tense in words. However, there are quite a few overlapping points. We tried to analyze the controversial points using KNN by looking at points that all their closest neighbors are from different class but it ain’t provided good enough distinction, seems like the words lost most of their meaning. We looked at the percentage of variance explained by each component and we observed that they actually explained very few of it. The variance explained by the first component is around 4.2% and the variance explained by the second component is around 3.4% so the overall percentage of variance explained is just around 7.6%! so by considering only those two components we barely preserve the essential characteristics of the original data. Nevertheless, it could be useful (although, not very successful) in terms of classification which suffix the word have.

## Word-similarities in Large Language Model

### Related words

In this part we compared word2vec and ChatGPT word similarity result.  
For each of the 5 words for which we generated the similarity lists in the word2vec part above (Computer, espresso, spy, run, game), we asked ChatGPT to produce a list of the 20 most similar words by itself. We did it word by word instead of asking for the all words in the same prompt.  
we started with the following prompt:  


As we can see, on the first try, for the word Computer, we got exactly 20 similar words, but we also got some phrases. So, we asked him again to give us similar words but this time without phrases and he succeeded.   
  
We can see that for acronym like PC (no.5), he just removed the interpretation when phrases like information technology (no.15) he just threw it away. Apart from those changes, the list is pretty the same.

We noticed that after asking from ChatGPT for ‘no phrases’ for the first time, for the rest of the words we didn’t receive any phrases. For example:   


From this word we kept asking the same question and got no phrases.

Both models give pretty accurate results for the similar words but have different approach for the similarity. it seems like word2vec similar words are more morphologically related words (the first words are always inflections of the query like tense, plurals, misspelling, capitals, etc.) while ChatGPT provides more semantically related words like synonyms.

In terms of diversity, on the one hand word2vec is lacking because it returns inflections of the word and because its based on co-occurrences and as a result he can return different words but in the same “type” (like a lot of runners names when query with run). On the other hand, ChatGPT sometimes produce duplicates words while with word2vec we always get words once (but it could be handle with another prompt).

There are some more differences in the similar words both models produce us.  
When asking for a word with initial cap, ChatGPT isn’t sensitive to it and refers to this word as the same word as lower caps, while for word2vec it gives different similar words for each one.   
Another one is that ChatGPT sometimes gives duplicates words as their most similar words.

(produced lists below)

|  |  |  |  |
| --- | --- | --- | --- |
| **Word** | **word2vec 20 most similar words (decreasing order)** | **ChatGPT 20 most similar words (decreasing order)** | **ChatGPT 20 most similar words without phrases (decreasing order)** |
| Computer | Computers, computer, Computing, Enterprises\_GoGrid\_Gomez, computers, Electronics, Genuitec\_Gizmox\_Glassbox\_Global, COMPUTER, Modules\_COMs, Information\_Technology, Microcomputer, Applied\_Computing, Lab\_International\_Concentsus, Marvell\_Plug, Microcomputers, Digital\_Forensics, PC, Malicious\_Attacks, Software, Laptops | Machine, Device, System, Processor, PC (Personal Computer), Laptop, Desktop, Mainframe, Server, Hardware, Software, Technology, Digital, Electronics, Information Technology, Workstation, Database, Network, Internet, Programming | Machine, Device, System, Processor, PC, Laptop, Desktop, Mainframe, Server, Hardware, Software, Technology, Digital, Electronics, Workstation, Database, Network, Internet, Programming, Coding |
| espresso | cappuccino, mocha, coffee, latte, caramel\_macchiato, ristretto, espressos, macchiato, chai\_latte, espresso\_cappuccino, caramel\_latte, vanilla\_latte, brewed\_coffee, iced\_coffee, nonfat\_latte, expresso, espresso\_latte, coffees, mocha\_latte, Lavazza\_coffee | Coffee, Brew, Shot, Beverage, Caffeine, Roast, Italian, Java, Cup, Barista, Crema, Aroma, Beans, Mocha, Latte, Americano, Macchiato, Cappuccino, Bar, Sip |  |
| spy | spies, spying, espionage, spymaster, CIA, Spy, MI6, spymasters, intelligence, CIA\_operative, eavesdropping, covert, persecute\_dissidents, counterspy, counterintelligence, supersecret, counterspies, KGB, honeytrap, superspy | Agent, Operative, Infiltrator, Mole, Sleuth, Spook, Informant, Saboteur, Covert, Espionage, Surveillance, Undercover, Intelligence, Detective, Reconnaissance, Secret, Cryptanalyst, Infiltration, Stealth, Clandestine |  |
| run | runs, running, drive, ran, scamper, tworun\_double, go, twoout, walk, Mark\_Grudzielanek\_singled, Batterymate\_Miguel\_Olivo, homerun, threerun, Collin\_Salzenstein, basesloaded, fielder's\_choice\_grounder, Peter\_Bourjos\_tripled, Casey\_Kalenkosky, Scutaro\_singled, clubbed\_solo\_homer | Sprint, Jog, Race, Dash, Rush, Marathon, Gallop, Trot, Pace, Stride, Jogger, Sprinter, Hurdle, Bolt, Scamper, Hasten, Hasten, Hurry, Propel, Zoom |  |
| game | games, play, match, matchup, agame, ballgame, thegame, opener, matches, tournament, playing, league, Game, scrimmages, fourgame, scrimmage, postseason, playoffs, gme, season | Play, Sport, Competition, Match, Recreation, Activity, Challenge, Gaming, Contest, Pastime, Amusement, Puzzle, Strategy, Tournament, Leisure, Entertainment, Plaything, Rivalry, Recreation, Contest |  |

Now we selected two of the words (run and espresso) and increased the number of neighbors from 20 to 100:

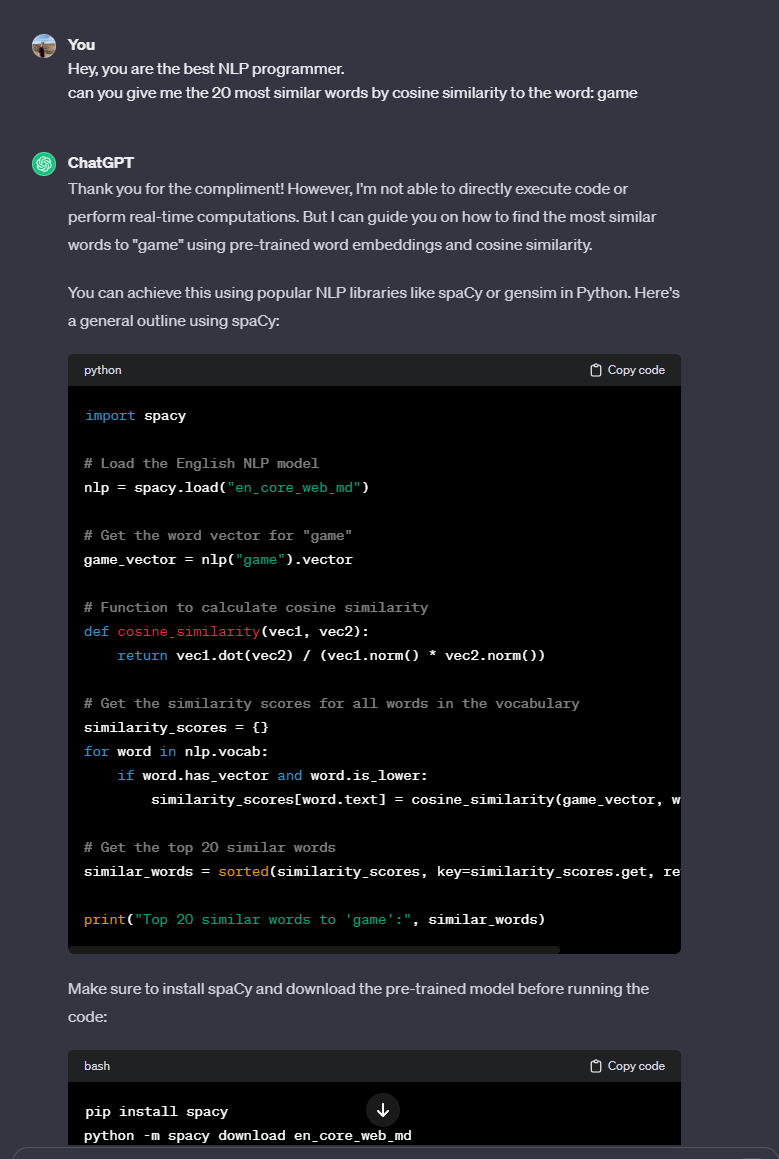
|  |  |  |
| --- | --- | --- |
| Word | **word2vec 100 most similar words (decreasing order)** | **ChatGPT 100 most similar words (decreasing order)** |
| run | runs, running, drive, ran, scamper, tworun\_double, go, twoout, walk, Mark\_Grudzielanek\_singled, Batterymate\_Miguel\_Olivo, homerun, threerun, Collin\_Salzenstein, basesloaded, fielder's\_choice\_grounder, Peter\_Bourjos\_tripled, Casey\_Kalenkosky, Scutaro\_singled, clubbed\_solo\_homer, Reliever\_Macay\_McBride, solo\_round\_tripper, Juan\_Uribe\_sacrifice\_fly, Melisa\_Koutz, Amonite, Geoff\_Blum\_sacrifice\_fly, roundtripper, ribbie, blooping\_single, Gelalich, Jonathan\_Lucroy\_singled, Alec\_Lowrey, DeSico, Earnest\_Rhone, Bucky\_Aona, Felix\_Fanaselle, Jed\_Lowrie\_sacrifice\_fly, blooped\_leadoff, Miguel\_Cabrera\_belted, Andy\_Schutzenhofer, Joey\_Swatfager, threerun\_homer, Edwin\_Encarnacion\_sacrifice\_fly, suicide\_squeeze\_bunts, Stack\_Babich, Sean\_Gusrang, Daniel\_Nottebart, Baron\_Batch\_tacked, Bo\_Cogbill, leftcenter, Omar\_Infante\_sacrifice\_fly, Nate\_Rolison, sacrifice\_fly, leadoff\_triple, Jose\_Tabata\_singled, Christina\_Capobianco, reliever\_Manny\_Parra, Cameron\_Seitzer, Ashley\_Razey, Micheal\_Dabbs, sac\_fly, Ronnie\_Belliard\_singled, Austin\_Kearns\_grounded, Gemoll, LaNinfa, Rich\_Aurilia\_singled, clubbed\_grand\_slam, Kenton\_Gedwed, Ronny\_Paulino\_singled, Grudzielanek\_singled, Russell\_Branyan\_belted, Brian\_Shouse\_relieved, Jorge\_Cantu\_sacrifice\_fly, Ryan\_Uphouse, Wigginton\_flied, trot, Span\_flied, Markakis\_homered, Matt\_Untiet, Ted\_Zentek, Deivi\_Cruz\_homered, solo\_homer, bullpen\_imploded, Yadier\_Molina\_grounded, sacrifice\_fly\_plated, Ellsbury\_looped, Matt\_Wieters\_sacrifice\_fly, Melvin\_Mora\_bunted, Jamie\_Keltz, Blake\_Hurlbutt, Batkoski, sacrfice\_fly, Matt\_Repec, Slumping\_slugger\_Carlos\_Pena, Hawpe\_homered, Hatteberg\_singled, Tyler\_Doke, Eugenio\_Velez\_infield, Casey\_McGehee\_singled, RBI\_groundout | sprint, jog, race, dash, rush, marathon, gallop, trot, pace, stride, jogger, sprinter, chase, flee, escape, hasten, accelerate, scamper, bolt, dart, hustle, scurry, lope, canter, amble, saunter, dash, jog, propel, hurtle, zoom, charge, fly, speed, navigate, travel, move, scuttle, barrel, tear, plod, lumber, strut, galumph, amble, meander, trudge, plod, hike, stroll, wander, cruise, traverse, cross, tread, step, saunter, march, amble, roam, journey, progress, proceed, advance, continue, explore, circulate, promenade, patrol, drift, wend, wind, snake, wiggle, ramble, dawdle, linger, shuffle, mosey, tramp, traipse, plow, forge, press, hustle, bustle, bustle, scramble, hustle, bustle, scramble, stir, surge, hustle, bustle, scramble, hustle, bustle, scramble, hasten |
| espresso | Coffee, Cappuccino, Latte, Americano, Macchiato, Mocha, Cortado, Ristretto, Affogato, Breve, Doppio, Lungo, Flat White, Turkish Coffee, Café au Lait, Irish Coffee, Red Eye, Vienna Coffee, Frappuccino, Turkish Coffee, Barista, Crema, Decaf, Froth, Baristress, Brew, Espresso Machine, Shot, Tiramisu, Crema, Mocha, Moka, Italian Roast, Arabica, Robusta, Filter Coffee, French Press, Cold Brew, Pour-over, Chemex, Coffee Bean, Espresso Cup, Coffeehouse, Bar, Blend, Grind, Roast, Barista, Cupping, Siphon Coffee, French Roast, Frother, Brewmaster, Coffee Roaster, Single Origin, Espresso Shot, Coffee Press, Coffee Pot, Demitasse, Coffee Connoisseur, Crema, Espresso Bar, Coffee Filter, Coffee Scoop, Coffee Grinder, Espresso Beans, Coffee Mill, Coffee Creamer, Coffee Syrup, Coffee Spoon, Coffee Napkin, Coffee Tumbler, Coffee Stirrer, Coffee Canister, Coffee Sack, Coffee Subscription, Coffee Sampler, Coffee Tasting, Coffee Fest, Coffee Roasting, Coffee Brewing, Coffee Culture, Coffee Ritual, Coffee Trade, Coffee Origin, Coffee Plantation, Coffee Harvest, Coffee Blend, Coffee Aroma, Coffee Flavor, Coffee Terroir, Coffee Bar, Coffee Break, Coffee Date, Coffee Hour, Coffee Snack, Coffee Dessert, Coffee Pairing, Coffee Moment, Coffee Ritual | cappuccino, mocha, coffee, latte, caramel\_macchiato, ristretto, espressos, macchiato, chai\_latte, espresso\_cappuccino, caramel\_latte, vanilla\_latte, brewed\_coffee, iced\_coffee, nonfat\_latte, expresso, espresso\_latte, coffees, mocha\_latte, Lavazza\_coffee, Knotty\_Bodies, cappuccinos, espresso\_machine, Caramel\_Macchiato, Espresso, chai\_tea\_latte, Starbucks\_coffee, frappuccino, latté, lattes, freshly\_brewed\_espresso, soy\_latte, barista, Illy\_coffee, smoothie, Frappuccino, decaf, mochaccino, espresso\_drinks, fresh\_brewed\_coffee, caramel\_mocha, iced\_mocha, grande\_mocha, skim\_latte, Lavazza\_espresso, cappuccino\_latte, latte\_mocha, java, Raspberry\_Mocha, liqueur, drip\_coffee, White\_Chocolate\_Mocha, café\_latte, espresso\_beverages, Iced\_Mocha, espressos\_lattes, capuccino, café\_mocha, squeezed\_juices, lattés, java\_junkies, cappucino, coffees\_lattes, gourmet\_coffee, flavored\_syrups, Espressos, brewed\_coffees, venti, caffe\_latte, freshly\_brewed\_coffee, o\_joe, frappuccinos, au\_lait, iced\_coffees, espresso\_beans, frothed\_milk, iced\_latte, gelato, raspberry\_mocha, cappuccinos\_lattes, squeezed\_orange\_juice, macchiatos, mocha\_frappuccino, mango\_smoothie, flavored\_lattes, barristas, Iced\_coffee, vanilla\_lattes, mocha\_lattes, frappucinos, lattes\_mochas, Caffe\_Mocha, Chai\_latte, venti\_mocha, crema, chocolate\_martini, caramel\_macchiatos, cappucinos, caffe\_mocha, java\_jolt |

We can see some trends in the data:

For the word “run” we can say that ChatGPT after 30 words starts repeating the same word multiple times while word2vec starts examples of runners.

For the word “espresso” we do see a similar trend that shows multiple types of coffee for both models.

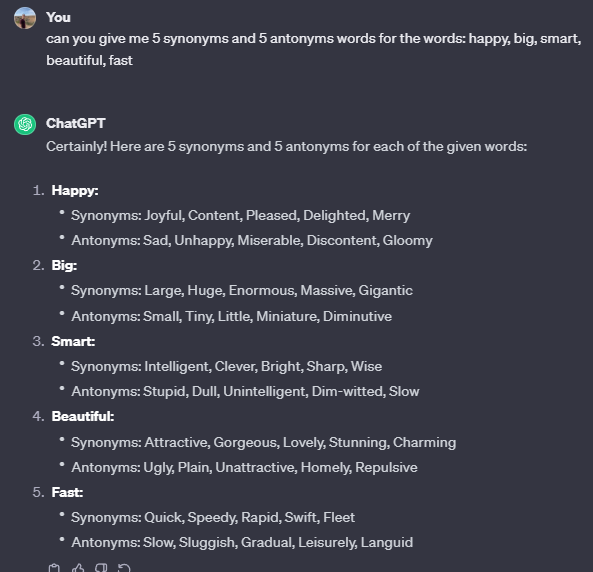
While working with ChatGPT we had to do make some adjustments with our prompts.   
for example, we tried to encourage him to give us good results, so we told him that he is the best programmer and asked for the most similar words by cosine similarity. The result was a code to do so instead of words. We also saw earlier how we had to ask it explicitly to remove phrases and not to duplicates words and so on.



### Synonyms and Antonyms

ChatGPT easily produced us multiple examples of Synonyms and Antonyms words with simple instructions of “can you give me 5 synonyms and 5 antonyms words for the words: happy, big, smart, beautiful, fast”.

|  |  |  |
| --- | --- | --- |
| Word | Synonyms | Antonyms |
| Happy | Joyful, Content, Pleased, Delighted, Merry | Sad, Unhappy, Miserable, Discontent, Gloomy |
| Big | Large, Huge, Enormous, Massive, Gigantic | Small, Tiny, Little, Miniature, Diminutive |
| Smart | Intelligent, Clever, Bright, Sharp, Wise | Stupid, Dull, Unintelligent, Dim-witted, Slow |
| Beautiful | Attractive, Gorgeous, Lovely, Stunning, Charming | Ugly, Plain, Unattractive, Homely, Repulsive |
| Fast | Quick, Speedy, Rapid, Swift, Fleet | Slow, Sluggish, Gradual, Leisurely, Languid |



Polysemy

When asked ChatGPT for similarities for the polysemous words, like word2vec, for group 1 (where each word reflects both word meanings), we got multiple meanings, and for group 2 (words such that the top-10 neighbours of each word reflect only a single meaning), we see that it indeed gave only one meaning.  
Although the similar behavior, there some differences.  
in our experiment, ChatGPT is more diverse and return in one case more meanings than word2vec. In addition, for 2 out of 3 words in group 2 ChatGPT return the opposite meaning from word2vec.

|  |  |  |  |
| --- | --- | --- | --- |
| Word | Word Group | **possible senses** | **ChatGPT 10 most similar words (decreasing order)** |
| mole | Group 1 | small burrowing mammal, a common type of skin growth, spy, unit in chemistry | Burrow, Rodent, Tunneler, Dermatologist, Spy, Spot, Blemish, Nevus (a type of skin mole), Underground, Molehill |
| bass | Group 1 | type of fish, low-pitched musical instrument, low voice | Low, Deep, Resonant, Fish, Sound, Musical, Pitch, Notes, Frequency, Double bass |
| fall | Group 1 | season (also known as autumn), to drop or descend | Autumn, Descend, Drop, Plummet, Tumble, Decline, Collapse, Autumnal, Precipitate, Topple |
| rock | Group 2 | A relatively hard naturally occurring mineral material, music genre | Stone, Boulder, Pebble, Cliff, Granite, Mineral, Formation, Geology, Mountain, Limestone |
| bar | Group 2 | drinking establishment, a straight piece (as of wood or metal) that is longer than it is wide (beam\rod) | Pub, Tavern, Saloon, Lounge, Counter, Establishment, Inn, Club, Public house, Watering hole |
| plant | Group 2 | botanical organism (seed), factory | Flora, Greenery, Botanical, Vegetation, Foliage, Herb, Shrub, Flower, Crop, Garden |

Reflected sense are represented by colors

Mean Average Precision (MAP) evaluation

In this part we chose 2 of the 5 words above, run and game. Then we generated lists of the 20 most similar words for each one by each method (word2vec and ChatGPT).  
we judged the correctness of their similarities manually, by two approaches: topically related and same semantic class.

run:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| word2vec | Topically related | Same semantic class | ChatGPT | Topically related | Same semantic class |
| runs | 1 | 1 | Sprint | 1 | 1 |
| running | 1 | 1 | Jog | 1 | 1 |
| drive | 0 | 0 | Race | 1 | 0 |
| ran | 1 | 1 | Dash | 1 | 1 |
| scamper | 1 | 1 | Rush | 1 | 1 |
| tworun\_double | 0 | 1 | Marathon | 1 | 0 |
| go | 1 | 1 | Gallop | 1 | 0 |
| twoout | 0 | 0 | Trot | 1 | 1 |
| walk | 1 | 1 | Pace | 1 | 1 |
| Mark\_Grudzielanek\_singled | 1 | 0 | Stride | 1 | 0 |
| Batterymate\_Miguel\_Olivo | 1 | 0 | Jogger | 1 | 1 |
| homerun | 1 | 1 | Sprinter | 1 | 1 |
| threerun | 1 | 0 | Hurdle | 1 | 0 |
| Collin\_Salzenstein | 1 | 0 | Bolt | 1 | 0 |
| basesloaded | 0 | 0 | Scamper | 1 | 0 |
| fielder's\_choice\_grounder | 0 | 0 | Hasten | 1 | 1 |
| Peter\_Bourjos\_tripled | 1 | 0 | Hasten | 1 | 1 |
| Casey\_Kalenkosky | 1 | 0 | Hurry | 1 | 1 |
| Scutaro\_singled | 1 | 0 | Propel | 1 | 0 |
| clubbed\_solo\_homer | 0 | 0 | Zoom | 0 | 0 |
| AP (average precision) |  |  |  |  |  |

game:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| word2vec | Topically related | Same semantic class | ChatGPT | Topically related | Same semantic class |
| games | 1 | 1 | Play | 1 | 1 |
| play | 1 | 1 | Sport | 1 | 0 |
| match | 1 | 1 | Competition | 1 | 0 |
| matchup | 1 | 1 | Match | 1 | 1 |
| agame | 1 | 1 | Recreation | 0 | 0 |
| ballgame | 1 | 1 | Activity | 0 | 0 |
| thegame | 1 | 1 | Challenge | 0 | 0 |
| opener | 1 | 0 | Gaming | 1 | 1 |
| matches | 1 | 1 | Contest | 1 | 0 |
| tournament | 1 | 0 | Pastime | 0 | 0 |
| playing | 1 | 0 | Amusement | 0 | 0 |
| league | 1 | 0 | Puzzle | 1 | 0 |
| Game | 1 | 1 | Strategy | 0 | 0 |
| scrimmages | 0 | 0 | Tournament | 1 | 0 |
| fourgame | 1 | 1 | Leisure | 0 | 0 |
| scrimmage | 0 | 0 | Entertainment | 1 | 0 |
| postseason | 1 | 0 | Plaything | 0 | 0 |
| playoffs | 1 | 0 | Rivalry | 0 | 0 |
| gme | 1 | 1 | Recreation | 0 | 0 |
| season | 1 | 0 | Contest | 1 | 0 |
| AP (average precision) |  |  |  |  |  |

Mean Average Precision (MAP):

|  |  |  |
| --- | --- | --- |
|  | Word2vec | ChatGPT |
| Topically related |  |  |
| Same semantic class |  |  |

So, in our experiment XXXX is better. But it important to note that 2 words are not representative, and we can’t really conclude that XXXX is better in overall.