# Mining cultural insights from online texts

Big Data Science @ SDSU
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“According to Computer World, **unstructured** information may account for more than 70% to 80% of all data in organizations. These data, which mostly originate from social media, constitute 80% of the data worldwide and account for 90% of Big Data.”

Khan, Yaqoob, Hashem, et al., “Big Data: Survey, Technologies, Opportunities, and Challenges,” *The Scientific World Journal,* vol. 2014, Article ID 712826, 18 pages, 2014.

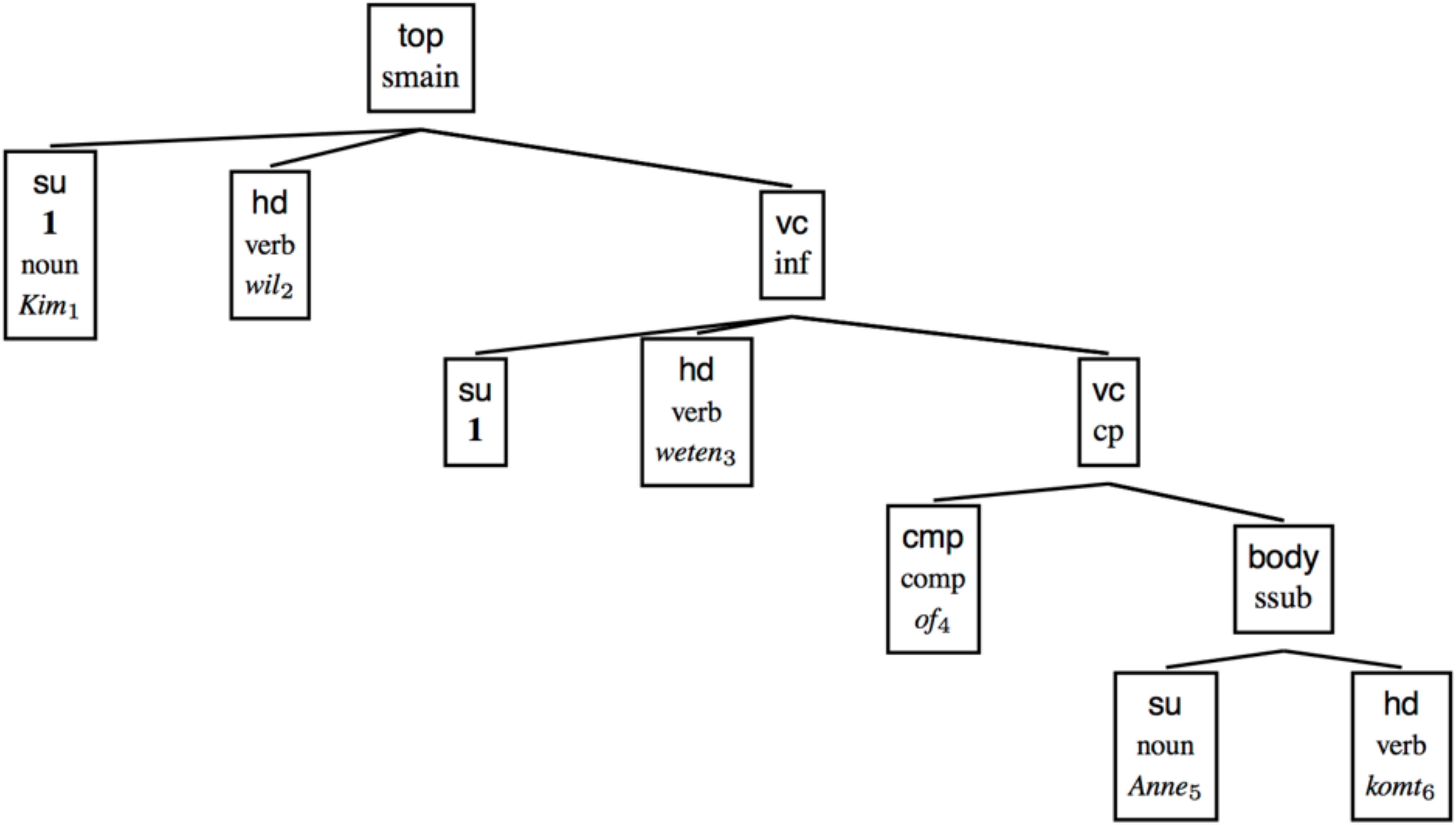



Figure 2: Dependency tree voor de zin *Kim wil weten of Anne komt*

van der Beek, Bouma, Malouf, and van Noord. 2002. "The Alpino Dependency Treebank." In *Computational Linguistics in the Netherlands 2001*. Pages 8-22.

# Computational linguistics

Natural Language Processing: Make information contained linguistically structured data available for further processing

Deep analysis vs. shallow analysis

- Quality of results
- Implementation difficulty
- Scalability


PIENSE
THINK
ДУМАЙ
सोचिए
$0
KEN
$1,200
WATSON
$0
BRAD

# Meaning

Shallow methods scale to billions or trillions of words ("There's no data like more data!")

Start from scratch and bootstrap linguistic knowledge

- Word meanings
- Phrase types
- Constructions

After linguistic patterns are established, we can extract real-world knowledge from texts

"You shall know a word by the company it keeps."

(J.R. Firth, 1957)

$$
\begin{array}{c|l}
\textit{Terms} & \qquad\qquad\qquad \textit{Documents} \\
 & \quad D_1 \quad\; D_2 \qquad\quad \cdots \qquad\quad\; D_m \\
\hline
\begin{array}{c} W_1 \\ \\ W_2 \\ \vdots \\ W_n \end{array} &
\begin{pmatrix}
\mathbf{C}_1^1 & \mathbf{C}_2^1 & \cdots & \mathbf{C}_j^1 & \cdots & \mathbf{C}_m^1 \\
 & & \vdots & & & \\
\mathbf{C}_1^i & \mathbf{C}_2^i & \cdots & \mathbf{C}_j^i & \cdots & \mathbf{C}_m^i \\
 & & \vdots & & & \\
\mathbf{C}_1^n & \mathbf{C}_2^n & \cdots & \mathbf{C}_j^n & \cdots & \mathbf{C}_m^n
\end{pmatrix} = \mathbf{C}
\end{array}
$$

(a) Typical term-document incidence matrix $\mathbf{C}$ ($\mathbf{C}_j^i = n \leftrightarrow$ document $D_j$ contains term $W_i$ exactly $n$ times)

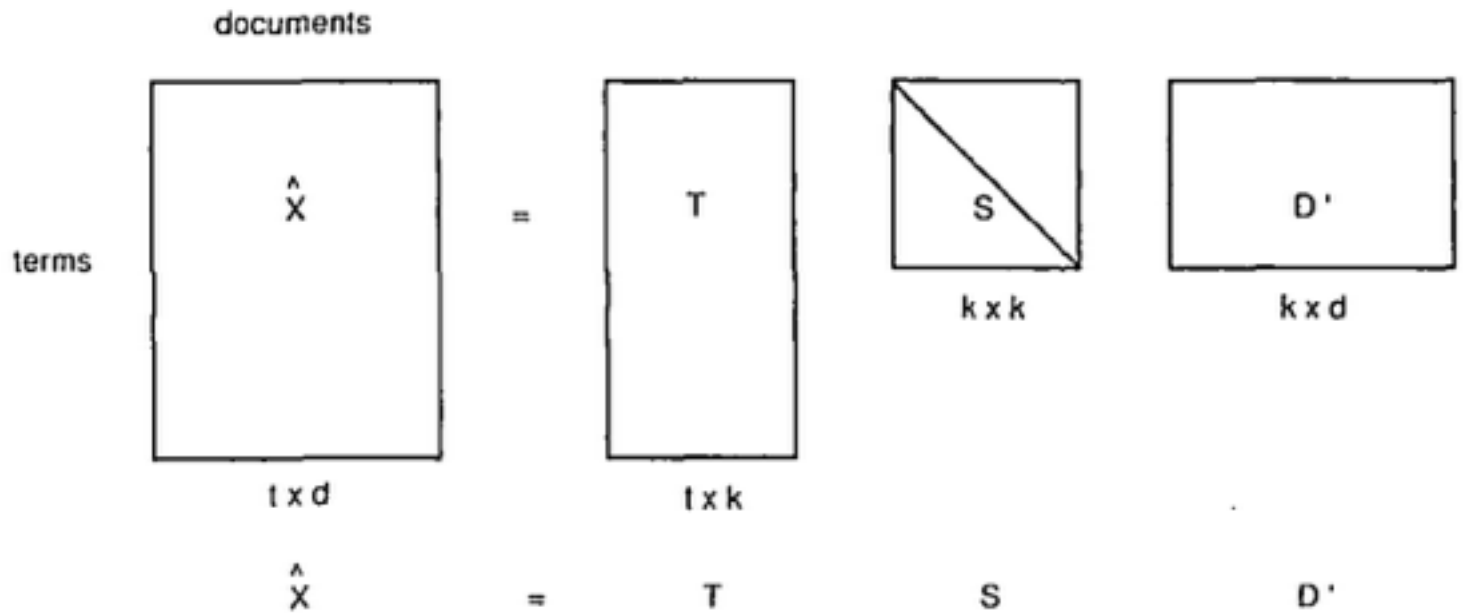
$$
\begin{array}{c|l}
\textit{Terms} & \qquad\quad \textit{Terms} \\
 & \; W_1 \quad W_2 \quad \cdots \quad W_n \\
\hline
\begin{array}{c} W_1 \\ \\ W_2 \\ \vdots \\ W_n \end{array} &
\begin{pmatrix}
\mathbf{R}_1^1 & \mathbf{R}_2^1 & \cdots & \mathbf{R}_n^1 \\
 & & & \\
\mathbf{R}_1^2 & \mathbf{R}_2^2 & \cdots & \mathbf{R}_n^2 \\
 & & \vdots & \\
\mathbf{R}_1^n & \mathbf{R}_2^n & \cdots & \mathbf{R}_n^n
\end{pmatrix} = \mathbf{R}
\end{array}
$$

(b) Typical term-term similarity matrix $\mathbf{R}$

$$\left(\mathbf{R}_j^i = \mathbf{R}_i^j = \sum_{k=1}^{m} \mathbf{C}_k^i \mathbf{C}_k^j \Big/ \sqrt{\left(\sum_{k=1}^{m} (\mathbf{C}_k^i)^2 \sum_{k=1}^{m} (\mathbf{C}_k^j)^2\right)}\right)$$

FIG. 2. Matrices used for the generation of term associations

Gerard Salton. 1963. “Associative Document Retrieval Techniques Using Bibliographic Information.” *J. ACM* 10, 4 (October 1963), 440-457.




**Reduced** singular value decomposition of the term x document matrix, X. Where:

T has orthogonal, unit-length columns ($T'T = I$)
D has orthogonal, unit-length columns ($D'D = I$)
S is the diagonal matrix of singular values
t is the number of rows of X
d is the number of columns of X
m is the rank of X ($\leq \min(t,d)$)
k is the chosen number of dimensions in the reduced model ($k \leq m$)

FIG. 3. Schematic of the *reduced* Singular Value Decomposition (SVD) of a term by document matrix. The original term by document matrix is *approximated* using the $k$ largest singular values and their corresponding singular vectors.

S. Deerwester, S.T. Dumais, G.W. Furnas, T.K. Landauer and R. Harshman (1990). "Indexing by Latent Semantic Analysis." *Journal of the American Society for Information Science*, 41(6), 391-407

# Vector Space Models

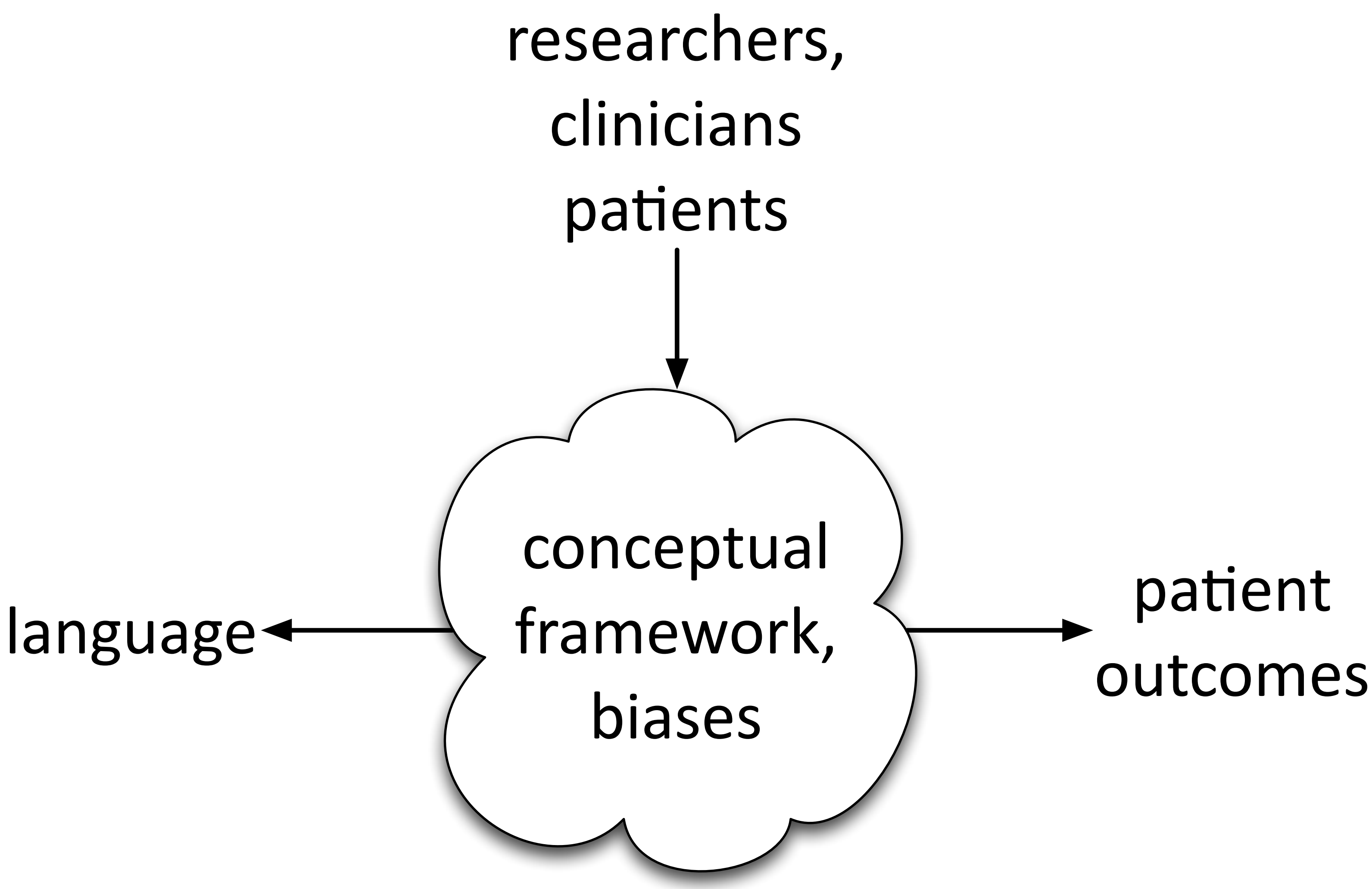
Vector Space Models are one way to operationalize Firth's distributional notion of meaning

Results from shallow methods can only be as good as the input (representativeness)

Corpus of reading material for K-12 students

- **bicycle**: pedals, handlebars, bicycles, pedaling, bike, starley, highwheeler, boneshaker, mede, lallement, gearwheels, gearwheel, drais, bikers, bikes, wheels, wheel, bicycled, pedal

- **patriot**: 1775, patriots, lexington, concord, loyalist, loyalists, 1777, bunker, minutemen, hancock, 1776, redcoats, ticonderoga, sniping, framingham, edgel, revere, cornwallis, saratoga




Malouf, Edwards, Perez Ruiz, Richette, Southam, and DiChiara. “A computational lexical analysis of the language commonly used to describe gout.” (submitted)


MIND-FUCKING TRAFFIC
WINO EXPRESSWAY
THE 1%
OLD MAN PENIS
PINOY THUG LIFE
AVOCADOS & RELIGIOUS EXTREMISTS
THE MALL
FIGHTER JETS & FURNITURE STORES
JUST TURN BACK NOW
COUGAR COUNTRY
99 RANCH
PROBABLY NOTHING
ALSO NOTHING
THE OUTBACK
"HEY BRAH"
WHERE FOOTBALL FANS HAVE THEIR DREAMS CRUSHED ANNUALLY
PIE
TRAILER PARK BEACH
TARGET VALLEY
A (KILLER) WHALE'S VAGINA
VEGAN FAIR TRADE HIPSTERS
WHERE THEY MAKE THE PORN
MEXICAN DISNEYLAND
TWINKS & FRUIT FLIES
CRAFT BEER HIPSTERS
PHO CORRIDOR
THE PEOPLE'S REPUBLIC OF OB
AIRPLANE RIDES THROUGH THE SKYLINE
YOUR DOCTOR'S OFFICE
GRASS & CULTURE
FIXED-GEAR BICYCLE HIPSTERS
HOT DOUCHES
TRANSIENT ALLEY
HANDLEBAR MUSTACHE HIPSTERS
SET OF TOP GUN
GUNS & BOATS
DOUCHEY HIPSTERS (DOUCHE-STERS)
BASICALLY MEXICO
RETIRED WHITES
LAS CUATRO MILPAS
SAN DIEGO, CALIFORNIA
MEXICO, LIKE FOR REALS

GAWKER

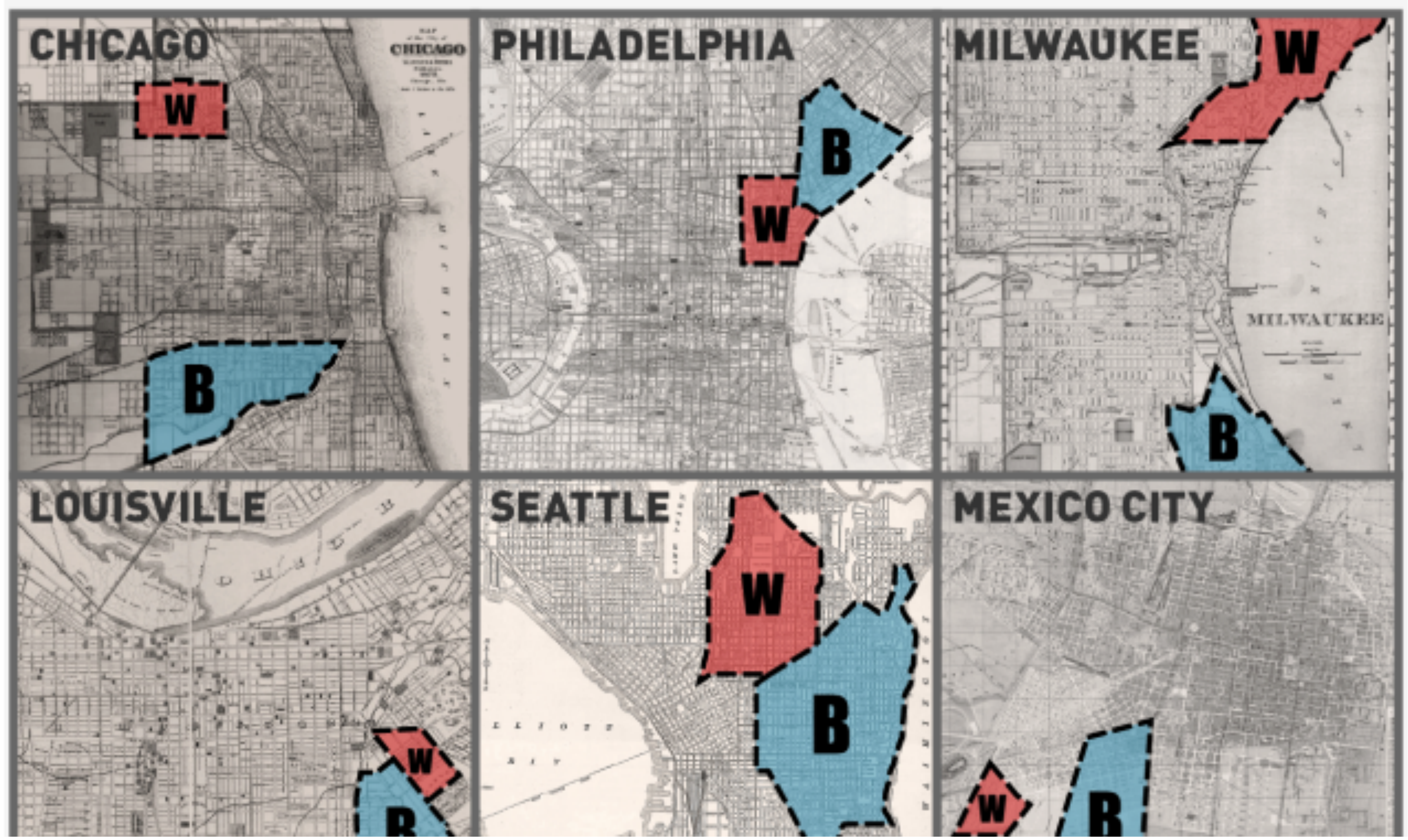
+ FOLLOW

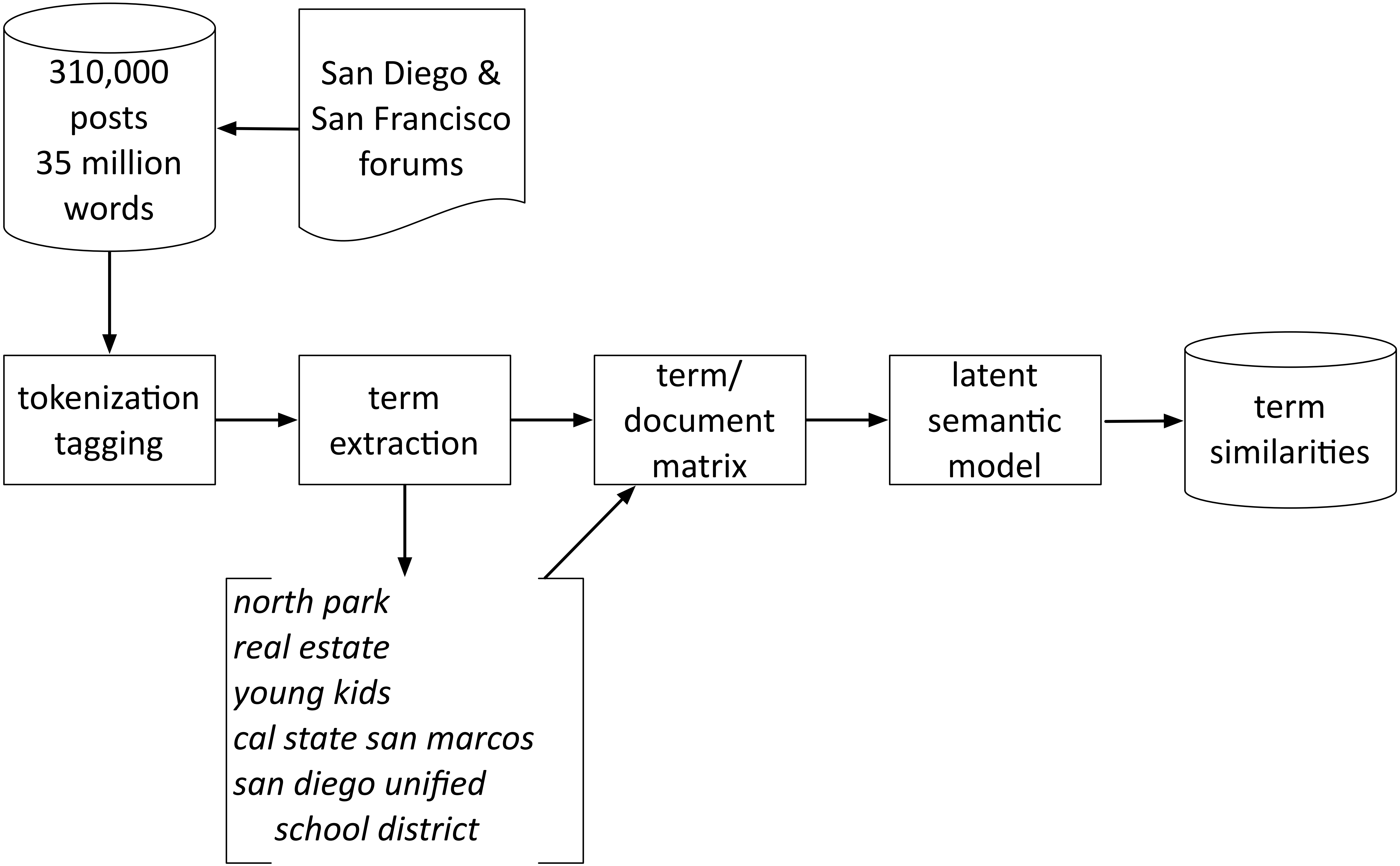
# This Is the Williamsburg of Your City: A Map of Hip America

Max Read

Filed to: WILLIAMSBURG 1/29/14 11:30am






310,000 posts 35 million words
San Diego & San Francisco forums
tokenization tagging
term extraction
term/ document matrix
latent semantic model
term similarities
north park
real estate
young kids
cal state san marcos
san diego unified school district

# north park

north park (0.000) south park (0.054) university heights (0.055) normal heights (0.096) golden hill (0.128) hillcrest (0.147) kensington (0.149) mission hills (0.177) adams ave (0.191) hipster (0.201) np (0.206) bankers hill (0.234) morley field (0.240) adams avenue (0.322) other neighborhoods (0.353) banker (0.360) craftsman (0.367) burlingame (0.369) park west (0.372) adams (0.373) gentrified (0.381) nh (0.384) flight path (0.385) coffee shops (0.385) funky (0.402) artsy (0.418) cottage (0.431) neighborhoods (0.438) little italy (0.444) mewzikguy (0.454) housing stock (0.456) iffy (0.458) walkable (0.459) gritty (0.459) bungalow (0.462) damon (0.463) urban (0.468) hip (0.482) main drag (0.489) hoods (0.492) hillcrest area (0.494) university avenue (0.498) uh (0.502) neighborhood (0.505) kettlepot (0.506) university ave (0.508) hipsters (0.521) mansions (0.529) apartment buildings (0.532) pubs (0.538) charm (0.541) sherman heights (0.548) park blvd (0.552) trendy (0.556) great neighborhood (0.562) talmadge (0.569) antique (0.569) univ (0.574) walkability (0.576) great areas (0.581) character (0.586) balboa park (0.590) parts (0.595) eclectic (0.606) gay (0.607) bars (0.607) sp (0.608) ocean beach (0.609) tattoo (0.613) urban areas (0.618) pricier (0.618) shops (0.621) gentrification (0.626) counts (0.627) sketchy (0.628) cottages (0.630) particularly (0.634) coffee shop (0.634) beach communities (0.635) upscale (0.636) blocks (0.638) northpark (0.645) heights (0.645) cortez hill (0.648) central sd (0.650) urban neighborhoods (0.650) congested (0.652) bungalows (0.654) small city (0.655) vibe (0.662) charming (0.664) neighboring (0.666) reached (0.670) hood (0.672) northern part (0.673) hill (0.673) urban core (0.674) downside (0.675) rental budget (0.675) central san diego (0.677)

# north park

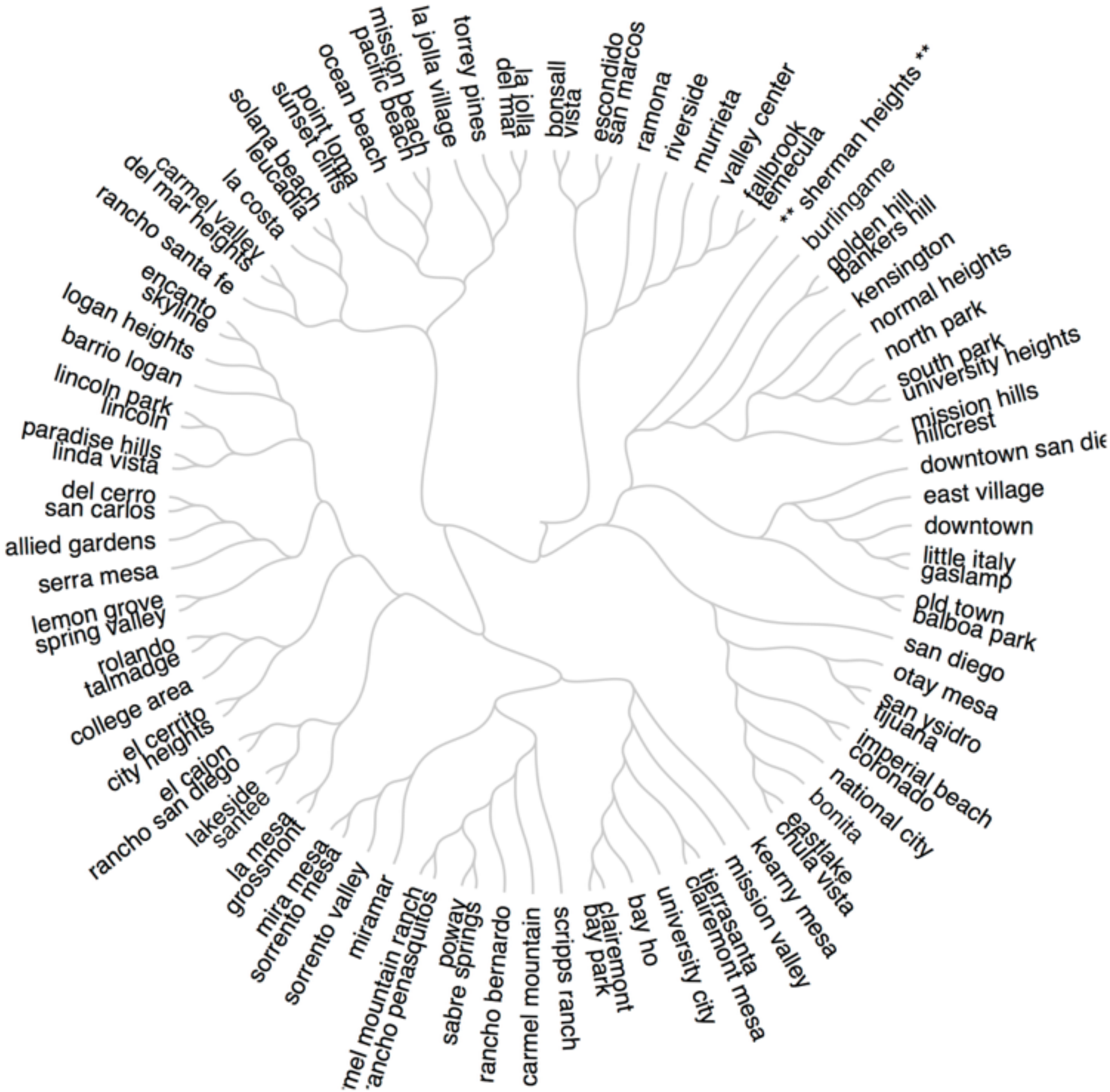
hipster (0.201) craftsman (0.367) gentrified (0.381) flight path (0.385) coffee shops (0.385) funky (0.402) artsy (0.418) cottage (0.431) housing stock (0.456) iffy (0.458) walkable (0.459) gritty (0.459) bungalow (0.462) urban (0.468) hip (0.482) main drag (0.489) hipsters (0.521) mansions (0.529) apartment buildings (0.532) pubs (0.538) charm (0.541) trendy (0.556) great neighborhood (0.562) antique (0.569) walkability (0.576) great areas (0.581) character (0.586) parts (0.595) eclectic (0.606) gay (0.607) bars (0.607) tattoo (0.613) urban areas (0.618) pricier (0.618) shops (0.621) gentrification (0.626) counts (0.627) sketchy (0.628) cottages (0.630) particularly (0.634) coffee shop (0.634) beach communities (0.635) upscale (0.636) blocks (0.638) urban neighborhoods (0.650) congested (0.652) bungalows (0.654) small city (0.655) vibe (0.662) charming (0.664) neighboring (0.666) reached (0.670) northern part (0.673) hill (0.673) urban core (0.674) downside (0.675) rental budget (0.675)

# clairemont mesa

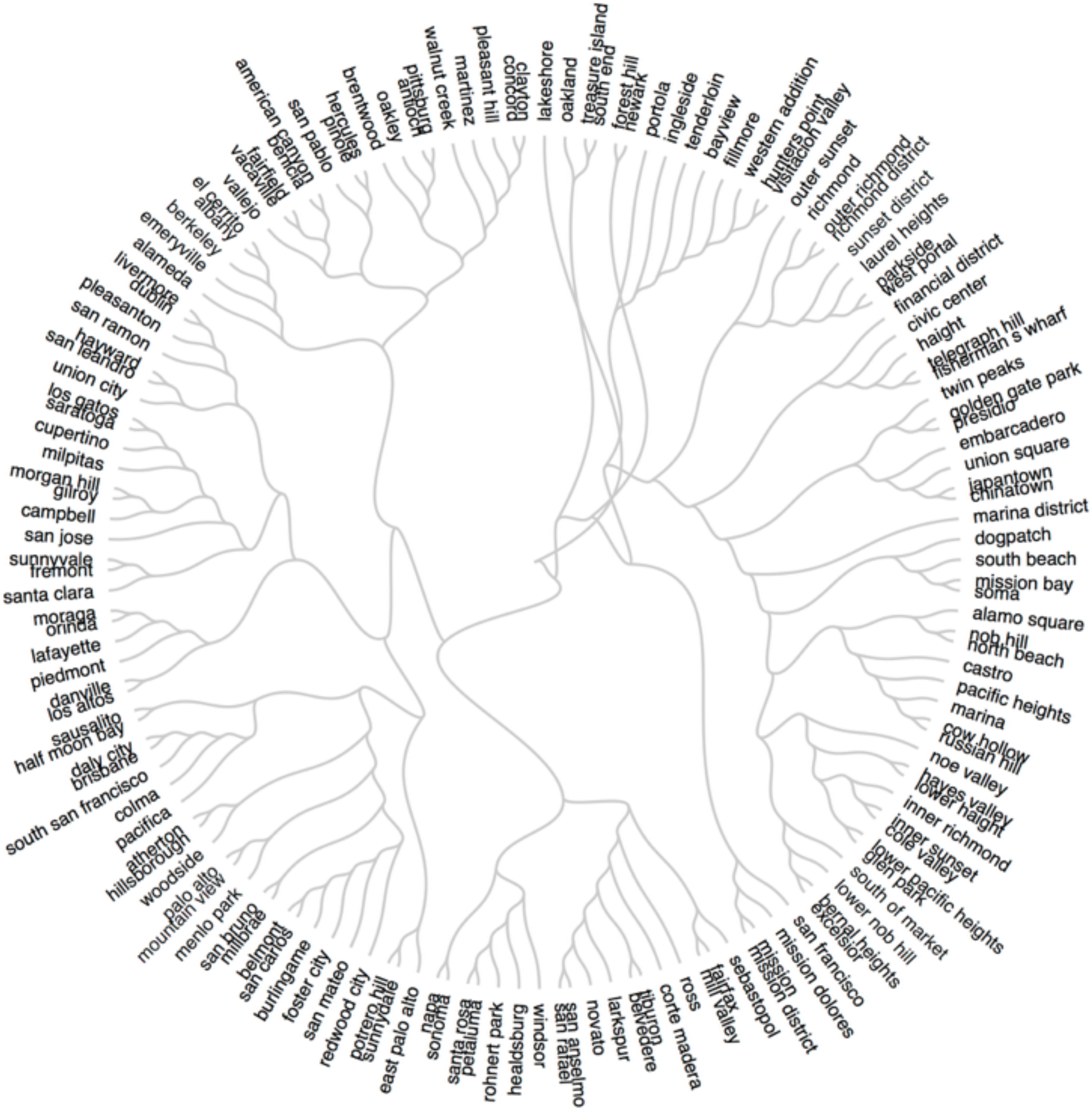
centrally (0.389) mesa college (0.459) apartment complexes (0.472) shopping centers (0.493) single family homes (0.512) supermarkets (0.512) located (0.519) supermarket (0.523) easy access (0.528) shopping malls (0.551) near (0.561) zip (0.562) branch (0.572) min drive (0.582) albertsons (0.608) apartments (0.609) good neighborhoods (0.614) branches (0.617) military housing (0.618) home depot (0.619) close (0.638) only one (0.640) classifieds (0.640) quiet (0.650) campus (0.656) henry (0.658) short commute (0.658) nasty (0.661) newly (0.661) complex (0.662) rush hour (0.663) short drive (0.663) repair (0.663) shopping center (0.665) pricey (0.669) condo complex (0.671) apts (0.671) item (0.680) recommended (0.682) centers (0.682) congestion (0.683) roommate (0.685) nearby (0.685) stores (0.686) parkway (0.688) ins (0.690) hey everyone (0.690) good area (0.691) pricier (0.691) mcdonalds (0.693) nicest (0.693)

# kearny mesa

chinese (0.247) korean (0.275) seafood (0.282) cuisine (0.287) authentic (0.313) sushi (0.316) convoy (0.325) japanese (0.325) thai (0.330) sandwiches (0.354) sauce (0.368) vietnamese (0.377) tasty (0.386) menu (0.389) good food (0.394) chef (0.397) hole (0.398) bread (0.415) cook (0.421) asian (0.428) cafe (0.431) food (0.435) grill (0.437) fresh (0.439) taco (0.444) deli (0.451) fries (0.462) mexican food (0.465) yelp (0.466) steak (0.472) restaurant (0.477) italian (0.478) burrito (0.481) wall (0.488) burger (0.491) ethnic (0.493) great food (0.495) cooked (0.495) french (0.498) strip mall (0.499) delicious (0.500) rolls (0.501) fried (0.502) beef (0.502) bacon (0.505) gems (0.510) cooking (0.511) asada (0.512) indian (0.514) filipino (0.515) egg (0.518) supermarkets (0.519) meat (0.520) eat (0.521) flavor (0.532) sandwich (0.534) chocolate (0.536) tacos (0.538) carne (0.540) burgers (0.543) dishes (0.546) fish (0.550) henry (0.552) portions (0.552) reservations (0.553) taco shop (0.553) lunch (0.554) rave (0.559) variety (0.560) el (0.560) eaten (0.560) pub (0.561) gourmet (0.562) chips (0.562) bakery (0.563) disappointed (0.564) chain (0.567) eating (0.567) mediocre (0.568) good places (0.570) try (0.572) breakfast (0.573) german (0.576) salad (0.581)



** sherman heights **
burlingame
golden hill
bankers hill
kensington
normal heights
north park
south park
university heights
mission hills
hillcrest
downtown san die
east village
downtown
little italy
gaslamp
old town
balboa park
san diego
otay mesa
san ysidro
tijuana
imperial beach
coronado
national city
bonita
eastlake
chula vista
kearny mesa
mission valley
tierrasanta
clairemont mesa
university city
bay ho
clairemont
bay park
scripps ranch
carmel mountain
rancho bernardo
sabre springs
poway
rancho penasquitos
rmel mountain ranch
miramar
sorrento valley
sorrento mesa
mira mesa
grossmont
la mesa
santee
lakeside
rancho san diego
el cajon
city heights
el cerrito
college area
talmadge
rolando
spring valley
lemon grove
serra mesa
allied gardens
san carlos
del cerro
linda vista
paradise hills
lincoln
lincoln park
barrio logan
logan heights
skyline
encanto
rancho santa fe
del mar heights
carmel valley
la costa
leucadia
solana beach
sunset cliffs
point loma
ocean beach
pacific beach
mission beach
la jolla village
torrey pines
del mar
la jolla
vista
bonsall
san marcos
escondido
ramona
riverside
murrieta
valley center
temecula
fallbrook


lakeshore
oakland
treasure island
south end
forest hill
newark
portola
ingleside
tenderloin
bayview
fillmore
western addition
hunters point
visitacion valley
outer sunset
richmond
outer richmond
richmond district
sunset district
laurel heights
parkside
west portal
financial district
civic center
haight
telegraph hill
fisherman s wharf
twin peaks
golden gate park
presidio
embarcadero
union square
japantown
chinatown
marina district
dogpatch
south beach
mission bay
soma
alamo square
nob hill
north beach
castro
pacific heights
marina
cow hollow
russian hill
noe valley
hayes valley
lower haight
inner richmond
inner sunset
cole valley
lower pacific heights
glen park
south of market
lower nob hill
bernal heights
excelsior
san francisco
mission dolores
mission
mission district
sebastopol
fairfax
mill valley
ross
corte madera
tiburon
belvedere
larkspur
novato
san anselmo
san rafael
windsor
healdsburg
rohnert park
santa rosa
petaluma
napa
sonoma
east palo alto
potrero hill
sunnyvale
redwood city
san mateo
foster city
burlingame
belmont
san carlos
san bruno
millbrae
menlo park
palo alto
mountain view
woodside
atherton
hillsborough
pacifica
colma
south san francisco
daly city
brisbane
sausalito
half moon bay
danville
los altos
piedmont
lafayette
moraga
orinda
santa clara
sunnyvale
fremont
san jose
campbell
morgan hill
gilroy
milpitas
cupertino
los gatos
saratoga
union city
hayward
san leandro
san ramon
pleasanton
dublin
livermore
alameda
emeryville
berkeley
el cerrito
albany
vallejo
fairfield
vacaville
american canyon
benicia
san pablo
hercules
pinole
brentwood
oakley
pittsburg
antioch
walnut creek
martinez
pleasant hill
clayton
concord

| | San Diego | San Francisco |
|---|---|---|
| *hipster* | south park | mission |
| *dim sum* | kearny mesa | chinatown |
| *affordable* | (temecula) | gilroy |
| *pricey* | del mar | pleasant hill |
| *dangerous* | logan heights | tenderloin |
| *tourist* | old town | union square |
| *condos* | downtown | soma |
| *gay* | hillcrest | (castro) |
| *good schools* | carmel mountain ranch | san ramon |
| *hiking* | ocean beach | presidio |
| *white collar* | sorrento valley | walnut creek |
| *flight path* | bankers hill | (burlingame) |

# Prospects

Big data linguistic techniques applied to broad spectrum texts allow us to extract real-world intelligence from ‘unstructured’ data

When applied to more focused corpora, they yield insights about speakers that would not be accessible via traditional qualitative methods

Hybrid quantitative / qualitative methods