Finding the best name for a set of words automatically

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Motivation

- many NLP applications contains set of words as a result
- clusters of words/lemmata
- they have common *meaning*, there is a name/label
- we want to find the name automatically

Sketch Engine Thesaurus

milk *(noun)* **British National Corpus freq = 4692** (41.8 per million)

Lemma	Score	Freq	Cluster
meat	0.227	3690	fruit [0.177, 4989] vegetable [0.164, 2714] potato [0. bean [0.134, 1744] rice [0.126, 1537] tomato [0.114
coffee	0.222	6372	wine [0.221, 7123] tea [0.202, 8256] beer [0.199, 36 [0.19, 6655]
juice	0.207	1883	salt [0.128, 3263]
cream	0.201	3221	bread [0.198, 3668] sugar [0.196, 3685] cheese [0.1 butter [0.19, 2062] chocolate [0.153, 2316]
egg	0.191	6071	
oil	0.173	10126	coal [0.108, 5302] gas [0.101, 8082]
food	0.171	20774	fish [0.134, 10322] goods [0.11, 10052] product [0.1
soup	0.17	1405	sauce [0.137, 1597] salad [0.112, 1394]
water	0.144	34246	blood [0.133, 9780]
cake	0.143	3666	biscuit [0.13, 1567] sandwich [0.109, 1769]
stuff	0.137	6629	meal [0.114, 6532]

Word Sketch

break *(verb)* **British National Corpus freq = 18603** (165.8 per million)

object	7100	3.6
silence	243	9.12
deadlock *79*	105	8.42
impasse 16 stalemate 10		
leg *245*	499	8.15
arm 81 finger 24 neck 149		
spell	80	7.98
bone *105*	122	7.87
skin 17		
news	177	7.67
law *362*	982	7.61
agreement 34 code 36 contract 89 pattern 25 record 186 regulation 21 rule 229		
mould	52	7.6
heart	170	7.46
ankle *51*	81	7.45
wrist 30		
promise	67	7.4
ice	59	7.26
ground *136*	186	7.24
surface 50		

subject	5542	5.1
Thief	35	7.63
thief	41	7.46
dawn	36	7.35
fighting	39	7.25
war *230*	244	7.22
strike 14		
burglar *27*	33	7.12
intruder 6		
marriage	72	7.0
storm	36	6.98
hell	38	6.96
wave	50	6.7
fight	34	6.7
fire	74	6.53
raider *17*	23	6.44
attacker 6		
scuffle	14	6.32
scandal	20	6.24
blaze	15	6.22
row	35	6.15

and/or	377	0.1
bend	9	6.11
damage	6	4.93
enter	18	4.88
fall *18*	35	4.27
try 17		
make *72*	80	2.68
go 8		

part_trans	1520	13.8
down	704	8.27
up	569	6.81
off	146	6.71
in	24	3.9
out	60	3.78
over	10	3.3

part_intrans	4343	22.4
down	1591	9.39
through	193	8.92
off	532	8.49

pp_into-p	872	16.5
trot	17	8.84
grin *20*	58	7.84
smile 38		
gallop	6	7.31
applause	8	7.27
run	25	6.2
garage	8	6.03
laughter	6	5.62
song	12	5.05
thought *22*	28	5.03
speech 6		
flat	11	5.01
piece	22	4.79
tear	6	4.78
house *76*	196	4.63
bank 7 car 23 group 6 home 29 market 24 office 9 shop 15 team 7		
time	12	0.84

LDA Frames

EAT

0.554086
frame 1166

SUBJECT		OBJECT	
222		40	
0.794216	person	0.085888	food
0.010335	people	0.046396	meal
0.007963	one	0.01947	egg
0.005797	man	0.01947	breakfast
0.004342	who	0.01726	lunch
0.003409	woman	0.016846	dinner
0.002687	child	0.015189	fish
0.002519	that	0.013256	meat
0.002307	all	0.012289	potato
0.002215	someone	0.012151	cake

0.128011
frame 622

152		40	
0.027104	bird	0.085888	food
0.026926	dog	0.046396	meal
0.023538	animal	0.01947	egg
0.023181	fish	0.01947	breakfast
0.016049	cat	0.01726	lunch
0.014979	child	0.016846	dinner
0.013374	people	0.015189	fish
0.01266	prey	0.013256	meat
0.011947	man	0.012289	potato
0.011769	horse	0.012151	cake

Algorithm

1. for each word – find top similar words in the thesaurus
2. sum the score for each of similar words across all given words for any word is the word itself)
3. sort similar words according to the sums of scores
4. display the top items from the list

Results

input word set	output top names
oil coal gas	fuel-n 0.696 energy-n 0.536
Britain Scotland Europe England	country-n 4.189 area-n 3.308
apple pear orange	fruit-n 2.145 thing-n 1.441
procedure study analysis method programme	system-n 5.367 work-n 4.959
pint bottle litre gallon	glass-n 2.371 water-n 2.258
meat fruit vegetable potato	food-n 3.291 fish-n 2.803
village town	city-n 0.611

Conclusion

- we have algorithm for finding names for set of words
- it is language independent (statistical thesaurus needed)