



Name:	Silvana Yacoub	Maher Mohsen
ID	20201091	20200415
Course:	Processing of Formal	and Natural Languages

Assignment 3

• Comparison between results of Pre-trained Model and Scratch Trained Model:

# Apple:



#### Banana:

	Banana			Banana			
	Pre-Trained			Scratch			
Similar \	Words	Opposite Words	,	Similar V	Nords	Opposite Words	
Word	Similarity	Word	Similarity	Word	Similarity	Word	Similarity
manana	0.791431	Ä-KE	-0.05593	bananas	0.906352639	carpaccio	0.306893
Melt-Banana	0.756687	a.	-0.07534	ana	0.696177006	opi	0.200724
Manana	0.73553	573	-0.08744	dana	0.565537035	round	0.281394
Tanana	0.703046	Ig3	-0.09338	hana	0.551503062	692A	0.281071
Bealanana	0.695887	G77	-0.10044	alana	0.548280895	stud	0.27839
Sanana	0.67239	SNIP	-0.10055	nirvana	0.523530662	informative	0.278011
Rienana	0.663097	ell	-0.1033	tijuana	0.378118753	stock	0.276649
Atsinanana	0.65791	000	-0.10678	wena	0.343515515	fitness	0.275239
Banana	0.661495	8206	-0.10811	divine	0.343358874	correspond	0.273449
znana	0.647766	p.3	-0.10812	banish	0.341878921	euro	0.272179

### **Carrot:**

	Ca	rrot			Car	rot		
	Pre-Trained			Scratch				
Similar V	Vords	Opposite Words		Similar V	Vords	Opposite Words		
Word	Similarity	Word	Similarity	Word	Similarity	Word	Similarity	
parrot	0.789355	Vĵtu	0.191314	carre	0.629027307	wawa	0.386813	
Barcarrotas	0.739765	M.T	0.175971	arroz	0.505128086	hopefully	0.34141	
ParrotBebop	0.730022	FPK	0.147449	carrier	0.500409842	bull	0.335568	
Puchowe	0.725651	io.	0.132698	rot	0.441484809	oar	0.310998	
MDMA-d.Farrott	0.718509	.VĀL	0.132466	carte	0.422255099	subpar	0.303295	
garrote	0.708679	Версо	0.132166	cart	0.408090562	raunchy	0.301087	
Parrott	0.701624	Äonm	0.128625	arrow	0.372463584	wa	0.300551	
Scaparrott	0.697271	.P	0.128012	cart	0.367175281	sushland	0.292048	
carroures	0.693663	KĶĶ	0.125833	naked	0.361409621	familiar	0.291961	
Cottle	0.673952	bib	0.123073	carman	0.35940969	itt	0.288118	

### Dog:

506.								
	Dog			Dog				
	Pre-Trained				Scr	atch		
Similar	Words	Opposite Word	5	Similar V	Words	Opposite Words		
Word	Similarity	Word	Similarity	Word	Similarity	Word	Similarity	
hot	0.713217	esialgsena	-0.246	doggy	0.675956011	original	0.338421	
food	0.557006	eesrindlikus	-0.24708	og	0.62164855	removerweird	0.326707	
sugar	0.508893	osalisena	-0.24887	doggle	0.576689899	parfait	0.326359	
sucks	0.506942	ebat¤ielikus	-0.24927	fog	0.532251537	coverage	0.318855	
fucks	0.505417	kahebrigaadilisena	-0.25385	doc	0.434562325	hot	0.313637	
slutty	0.500833	autoriteedina	-0.25614	log	0.432422191	beverage	0.312301	
lazy	0.49334	fĀVĀVsikalisena	-0.25716	jog	0.42359069	slice	0.311053	
hairy	0.487935	aistitavana	-0.2622	uc	0.39166683	bullshit	0.308227	
drink	0.486259	temaatilisena	-0.26287	dock	0.390025705	origin	0.304616	
jumps	0.483448	kosmilises	-0.26601	dot	0.387280613	remodel	0.293834	

# Elephant:

	Eler	phant			
Pre-Trained					
Similar V	Vords	Opposite Words			
Word	Similarity	Word	Similarity		
elephants	0.820782	EVC	-0.06539		
Elephant	0.801807	Ä_gli	-0.08343		
elephantopus	0.747856	QSL	-0.08672		
Elephants	0.723123	Miy	-0.08763		
El©phant	0.694809	eSLi	-0.08893		
Aphantochroa	0.664167	ç□□å*¶éf;	-0.08953		
decaying	0.642105	KMi	-0.09113		
wood-decaying	0.641783	GÃn	-0.09307		
towels	0.634109	Hitu	-0.09784		
Elephantine	0.631994	ODUs	-0.0984		

Elep	hant			
Scratch				
Vords Opposite Words				
Similarity	Word	Similarity		
0.615853369	salsa	0.382636		
0.460246772	mixed	0.352083		
0.440311491	solitary	0.341221		
0.437695503	salsayum	0.336823		
0.408464015	marvelous	0.33362		
0.406095564	dairy	0.314222		
0.389703959	miami	0.30932		
0.38866064	salsas	0.309206		
0.377113909	michigan	0.301037		
0.370117009	balsamic	0.290748		
	Ser. Words Similarity 0.615653369 0.460240772 0.440311491 0.437695503 0.408464015 0.406095864 0.389703899 0.39866064 0.377113909	Nords		

# Flower:

	FI	ower			
Pre-Trained					
Similar '	Words	Opposite Word	s		
Word	Similarity	Word	Similarity		
wildflower	0.889169	loa•	-0.07092		
Blower	0.839807	54-	-0.08224		
Bellflower	0.830685	prg	-0.09646		
ReyMayflower	0.830608	p.3	-0.09828		
sunflower	0.82858	LOVL	-0.10724		
blower	0.82366	lg2	-0.11129		
Sunflower	0.815642	yelp	-0.11342		
Wildflower	0.809431	TTTS	-0.11423		
Flower	0.799598	0.72	-0.11565		
Moonflower	0.798604	PHP4	-0.11636		

	Flower					
	Scratch					
Similar Words Opposite Words						
Word	Similarity	Word	Similarity			
sunflower	0.826930702	declan	0.384936			
lower	0.747795284	budino	0.316453			
cauliflower	0.722260416	hibachi	0.311197			
tower	0.611448944	hasselhoffe	0.30887			
follower	0.561254919	deck	0.299655			
flow	0.555751324	little	0.292172			
power	0.542147219	similar	0.290821			
shower	0.525895119	motivation	0.278213			
flora	0.506107271	asopada	0.27195			
floral	0.464147329	significantly	0.271902			

# **Guitar:**

Gultar						
	Pre-Trained					
Similar	Words	Opposite Words	3			
Word	Similarity	Word	Similarity			
guitars	0.767422	0.72	-0.14034			
drums	0.675521	lga	-0.14463			
Guitar	0.647187	ELs	0.14468			
Kitar	0.632662	7916	-0.15028			
Sitar	0.627926	vĐ'hem	-0.1531			
goldrush	0.610903	p.3	-0.154			
sitar	0.610868	FIEt	-0.15686			
guitarra	0.60888	prg	-0.16095			
vocal	0.602663	140st	-0.16851			
swing	0.601596	SRKS	-0.17228			

	Gul	ltar				
	Scratch					
Similar \	Similar Words Opposite Words					
Word	Similarity	Word	Similarity			
guitarist	0.578969955	nod	0.309296			
tar	0.450099736	eart	0.296481			
ohmygoodness	0.397105813	bibimbop	0.283452			
tartar	0.395949066	budget	0.202493			
oar	0.392498642	granola	0.270708			
updo	0.377696425	budgetsavvy	0.268146			
goodness	0.376236439	office	0.26621			
restrictionsetc	0.370477498	ujs	0.26459			
gooda	0.360880822	eyebrow	0.261106			
sauvignon	0.359365702	budino	0.258516			

### House:

	Hou	use				
	Pre-Trained					
Similar	Words	Opposite Words				
Word	Similarity	Word	Similarity			
deep-house	0.757118	K-89	-0.21224			
art-house	0.719953	L-it	-0.21298			
Icehouse	0.712557	PdLi	-0.21347			
Dochouse	0.707282	35.1	-0.21573			
warehouse	0.701123	LV½	-0.21716			
Epic-house	0.688885	ĬΝΜ	-0.22597			
spouse	0.688839	XP31	-0.22791			
Hothouse	0.688695	HĀ*	-0.23141			
Henhouse	0.688074	3-lt	-0.23172			
farmhouse	0.684496	9,3.	-0.23309			

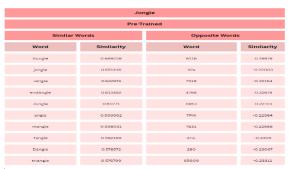
	House				
	Scr	atch			
Similar V	Vords	Opposite Words	s		
Word	Similarity	Word	Similarity		
madhouse	0.765157759	plan	0.321643		
inhouse	0.703049719	anytime	0.31359		
brewhouse	0.684699357	mite	0.304531		
douse	0.673374355	allan	0.304326		
townhouse	0.633041263	cilantro	0.287145		
steakhouse	0.623664187	significantly	0.276911		
housekeeper	0.621271193	lane	0.276219		
rittenhouse	0.610117137	death	0.276113		
smokehouse	0.602192521	bras	0.270667		
mouse	0.566097081	miracle	0.269016		

#### Internet:



Internet				
Scratch				
Similar Words		Opposite Words		
Word	Similarity	Word	Similarity	
intern	0.077772152	laura	0.308778	
internal	0.851165235	crabsjust	0.304799	
international	0.723920047	lack	0.30075	
interact	0.722835064	bartendress	0.295039	
interior	0.711758614	margarhita	0.294098	
interpret	0.651401877	salsas	0.287757	
interview	0.644109905	las	0.283306	
interpretation	0.56237179	crabmeat	0.280577	
intense	0.516855419	money	0.276402	
lantern	0.507934511	plateit	0.273227	

### Jungle:



Jungle Scratch				
Word	Similarity	Word	Similarity	
jingte	0.703954756	benefit	0.308654	
single	0.629478514	pad	0.284987	
dingle	0.61215502	winebytheglass	0.284635	
dangle	0.578898728	benedict	0.282613	
eagle	0.488679796	turkey	0.279675	
singletary	0.452142805	meat	0.278275	
google	0.442200141	bonchon	0.277519	
struggle	0.430143380	notice	0.275412	
yuengle	0.429861993	wealth	0.267525	
snuggle	0.391722232	weisswurst	0.267385	

# **Conclusion:**

The experiment underscores the effectiveness of pretrained word embeddings in capturing semantic information, highlighting their superiority over scratch-trained embeddings under similar training conditions.

- After training for 1500 epochs with a vector size of 100 and a window size of 10:
  - Pretrained word embeddings consistently outperformed scratch-trained embeddings.
- The results indicate that pretrained embeddings captured richer and more meaningful representations of words compared to scratch-trained embeddings.
- Leveraging pretrained embeddings offers advantages in terms of:
  - o Learning robust semantic relationships between words.
  - Reducing training time and computational resources.
  - Facilitating faster model development and deployment.