

## Sprachmodelle und Wort-Analogien

Mark Cieliebak

# Sprachmodelle haben beeindruckende Anwendungen



## Machine Translation



## Social Media Monitoring



## Internet Search



## Siri & Co.



## Email Spam Detection



## Emotional Robots

# Sprachmodelle lernt der Computer durch LESEN



# Ein Sprachmodell

can	0.5155	0.3922	0.5028	0.0754	0.2577	0.1081	0.4506	0.8543	0.8846	0.0735	0.6193	0.4665	0.0514	0.7233	0.0099	...
cancel	0.5322	0.1210	0.3636	0.7439	0.5725	0.8717	0.6490	0.2570	0.8216	0.0379	0.7010	0.5227	0.4154	0.0208	0.6943	...
cancer	0.8428	0.8249	0.1866	0.5433	0.2363	0.2876	0.0699	0.4021	0.3536	0.5550	0.8739	0.0676	0.1677	0.6342	0.0923	...
candidate	0.8666	0.0191	0.4946	0.2295	0.7789	0.9111	0.9861	0.3346	0.3630	0.6600	0.0986	0.5848	0.5875	0.4321	0.7821	...
candy	0.3189	0.1610	0.9404	0.3530	0.4365	0.7654	0.2500	0.5182	0.6641	0.5115	0.6963	0.8893	0.2031	0.9848	0.9100	...
cannot	0.5079	0.4045	0.2266	0.5008	0.8807	0.9993	0.5658	0.1223	0.9197	0.7432	0.8146	0.0170	0.8230	0.4321	0.6223	...
cap	0.2779	0.6267	0.9160	0.1734	0.6465	0.9158	0.0069	0.8747	0.2266	0.8204	0.6730	0.8763	0.0022	0.3199	0.0484	...
capable	0.9596	0.4305	0.4793	0.6468	0.7929	0.8989	0.1347	0.5853	0.3708	0.1799	0.8231	0.8921	0.2404	0.1599	0.1314	...
capacity	0.4897	0.1339	0.4320	0.0614	0.4611	0.9287	0.5865	0.1763	0.8463	0.0545	0.1887	0.7344	0.6176	0.9512	0.4871	...
capital	0.9512	0.0833	0.3092	0.1659	0.0421	0.7639	0.1220	0.4283	0.0398	0.8058	0.1165	0.5096	0.9672	0.2341	0.5635	...
captain	0.9397	0.5857	0.9925	0.5326	0.4376	0.9716	0.8523	0.2607	0.7638	0.7493	0.9601	0.9190	0.3447	0.1245	0.2801	...
capture	0.7114	0.0676	0.3310	0.1902	0.4096	0.8521	0.4033	0.9617	0.3120	0.5190	0.6215	0.4604	0.9345	0.6947	0.8225	...
car	0.0005	0.7991	0.5120	0.9244	0.4721	0.8163	0.8615	0.4768	0.8478	0.9161	0.3891	0.7498	0.9027	0.0978	0.6483	...
card	0.9763	0.6676	0.8416	0.6266	0.9205	0.1387	0.8243	0.9596	0.0505	0.7321	0.6015	0.2792	0.1946	0.6298	0.3299	...
cardboard	0.4977	0.2042	0.2347	0.2592	0.7314	0.1503	0.8643	0.6277	0.6528	0.3211	0.4284	0.6028	0.6579	0.3438	0.8679	...
care	0.0216	0.0397	0.9104	0.6622	0.5579	0.2447	0.8156	0.5961	0.6629	0.0037	0.1661	0.2409	0.4716	0.9933	0.0993	...
career	0.0714	0.9177	0.9954	0.2542	0.1337	0.2331	0.3211	0.3326	0.1933	0.8663	0.4766	0.1594	0.7823	0.4256	0.1565	...
careful	0.6943	0.1560	0.8262	0.2898	0.7068	0.1578	0.1624	0.5662	0.3325	0.9385	0.8462	0.7486	0.5997	0.4623	0.2557	...
carefully	0.3492	0.4429	0.1664	0.9426	0.0097	0.6261	0.8424	0.6461	0.1590	0.6048	0.6842	0.8323	0.7945	0.8261	0.5518	...
careless	0.6710	0.7272	0.2733	0.3674	0.2412	0.3951	0.6925	0.4001	0.4039	0.5197	0.7726	0.7053	0.3666	0.3052	0.7626	...
carelessly	0.6089	0.5111	0.9879	0.2249	0.6800	0.8130	0.5784	0.9545	0.4779	0.0664	0.2036	0.7427	0.1030	0.9314	0.9355	...
carpet	0.3812	0.3889	0.7021	0.9725	0.7991	0.7970	0.8733	0.1727	0.1407	0.0279	0.0106	0.9758	0.9660	0.2327	0.4367	...
carrot	0.7812	0.5279	0.7392	0.4465	0.7145	0.5353	0.4155	0.7697	0.3002	0.1780	0.2044	0.8343	0.9002	0.3512	0.4127	...
carry	0.9456	0.6843	0.1344	0.8874	0.6115	0.9514	0.8838	0.8683	0.6423	0.8614	0.1560	0.2350	0.4228	0.6077	0.3519	...
case	0.3617	0.8931	0.7898	0.2338	0.9778	0.1039	0.8316	0.9361	0.2614	0.2407	0.1572	0.3231	0.2880	0.5463	0.5149	...
cash	0.4424	0.2244	0.8616	0.7564	0.3774	0.0554	0.9152	0.1166	0.1737	0.5246	0.3976	0.6901	0.1335	0.4384	0.0897	...
cast	0.5727	0.7952	0.7037	0.4403	0.8816	0.4123	0.5694	0.2182	0.8957	0.1660	0.6692	0.4932	0.9080	0.5753	0.9519	...
castle	0.0807	0.7018	0.2580	0.1742	0.4891	0.3418	0.2245	0.2096	0.6284	0.8215	0.1285	0.1792	0.5564	0.6354	0.8945	...
cat	0.2349	0.3023	0.7348	0.0680	0.3166	0.6845	0.9944	0.0718	0.4963	0.1424	0.8737	0.6351	0.5867	0.5334	0.1291	...

# Text Understanding with Deep Learning

what is a car



Explain: <car>

# Text Understanding with Deep Learning

who is Albert Einstein



Explain: <Albert Einstein>



# Text Understanding with Deep Learning

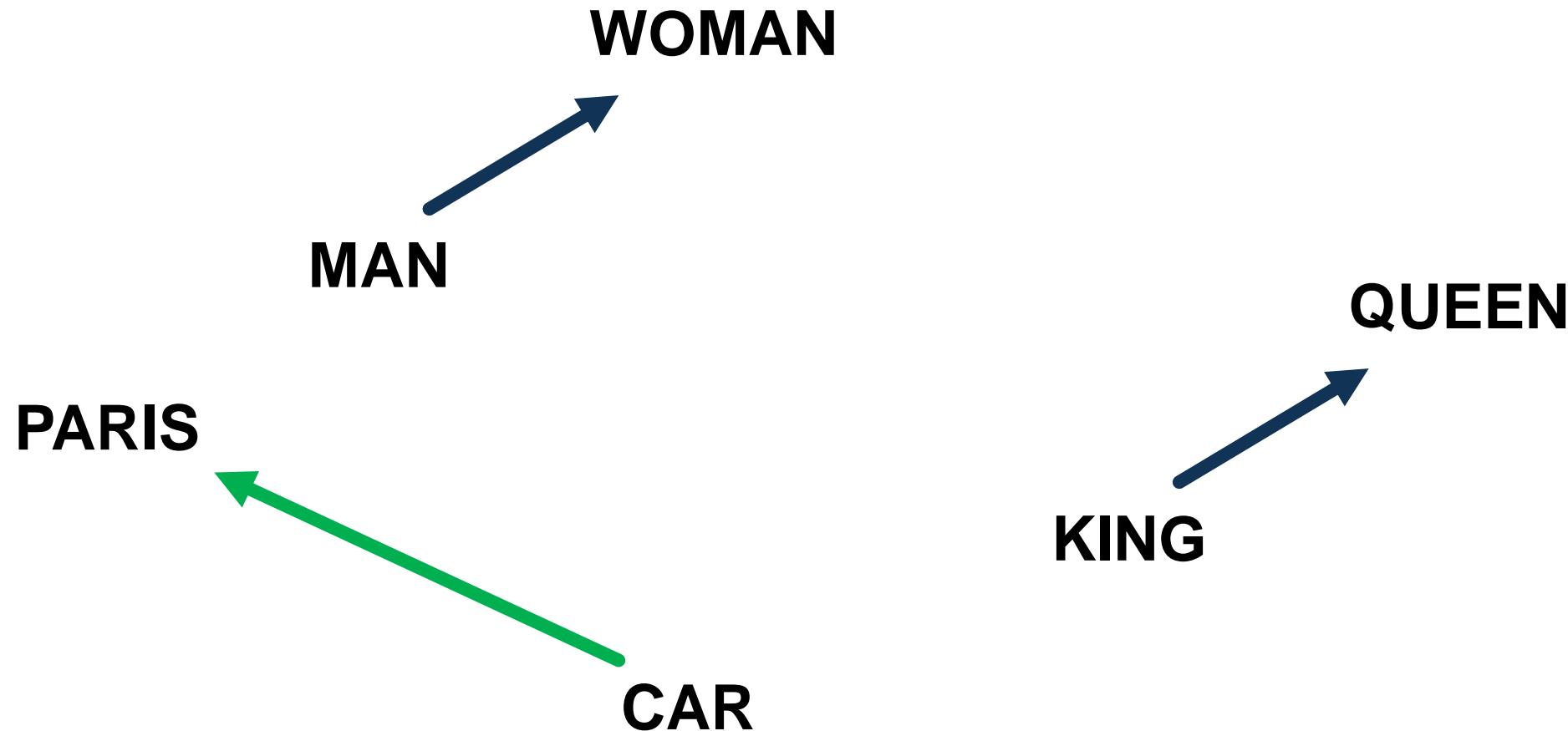
What is Zurich



Explain: <Zurich>



# Mit Wort-Analogien das Sprachmodell verstehen



# Text Understanding with Deep Learning

man is to king as woman is to|



Relation of <man> <king> and <woman>

man

is to

king

as

woman

is to

queen

# Text Understanding with Deep Learning

painter is to Picasso as composer is to



Relation of <painter> <Picasso> and <composer>

painter

is to

composer

is to

Mozart	0.66
Beethoven	0.66
composers	0.62
Leonard Bernstein	0.60
JS Bach	0.59
Diabelli Variations	0.59
Tchaikovsky	0.59

# Automatische Modelle "verstehen" Zusammenhänge

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

# Text Understanding with Deep Learning

Tell me the sentiment of "This is a nice day"



Sentiment of <"This is a nice day">

## Sentiment

Sentiment

Confidence

Positive



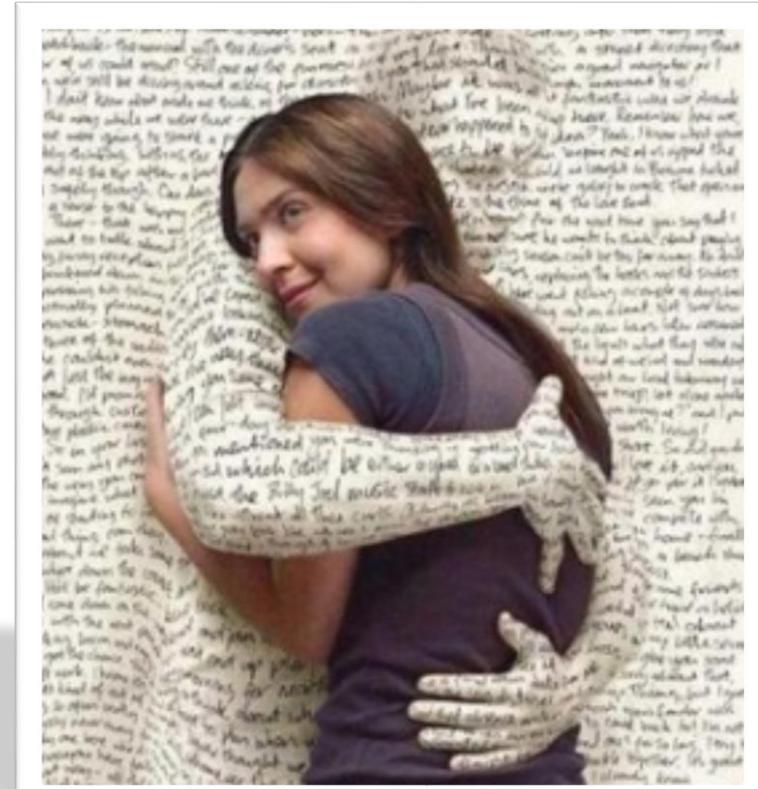
Neutral



Negative



# Vielen Dank für Ihre Aufmerksamkeit



Die Demo wird betrieben von der SpinningBytes AG, einem Spin-off der ZHAW.

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