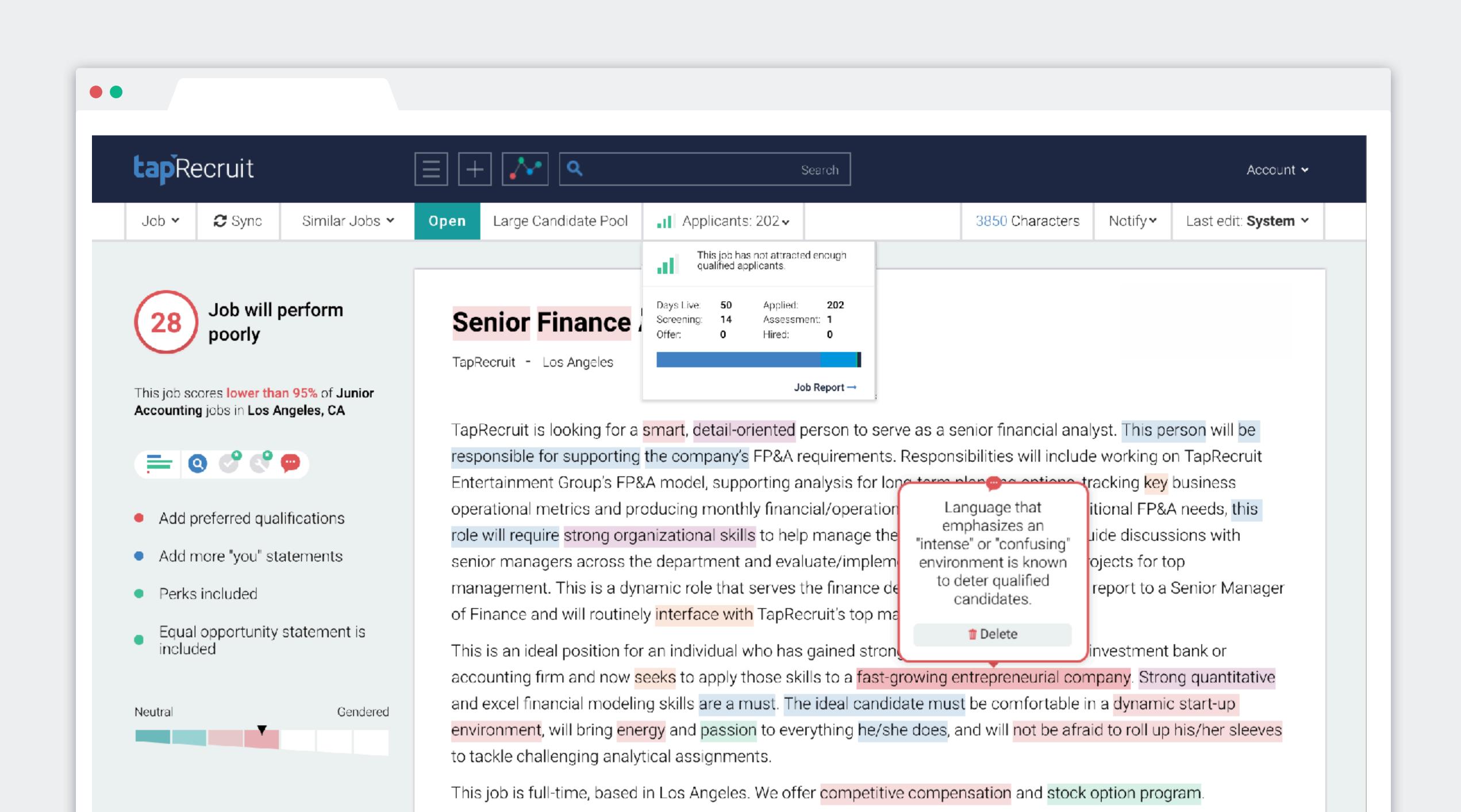
Beyond Word2Vec: Using embeddings to chart out the ebb and flow of tech skills

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Skills and qualifications matter in job descriptions

Same title, Different job







- Required Experience
- Required Responsibility
- Preferred Skill
- Required Education



Research at TapRecruit

Helping companies make fairer and more efficient recruiting decisions

NLP and Data Science:

- What are distinguishing characteristics of successful career documents?
- What skills are increasingly important for different industries?

Decision Science:

- How do candidates make decisions about which jobs to apply to?
- How do hiring teams make decisions about candidate qualifications?

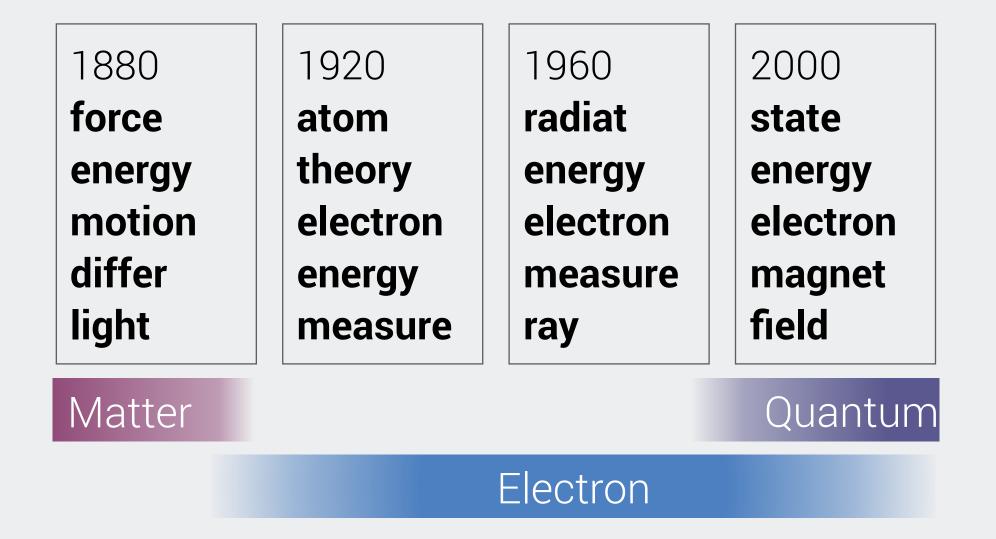


How have tech skills changed over time?

Strategies to identify changes among corpora

Traditional approaches do not capture syntactic and semantic shifts





Manual Feature Extraction

Require selection of key attributes, therefore difficult to discover new attributes

Dynamic Topic Models

Require experimentation with topic number



Embeddings use context to extract meaning

Window sizes capture semantic similarity vs semantic relatedness

Statistical modeling through software (e.g. SPSS) or programming language (e.g. **Python**)

Context

Word

Experience in **Python**, Java or other object-oriented programming languages

Context

Context

Proficiency programming in **Python**, Java or C++.

Context

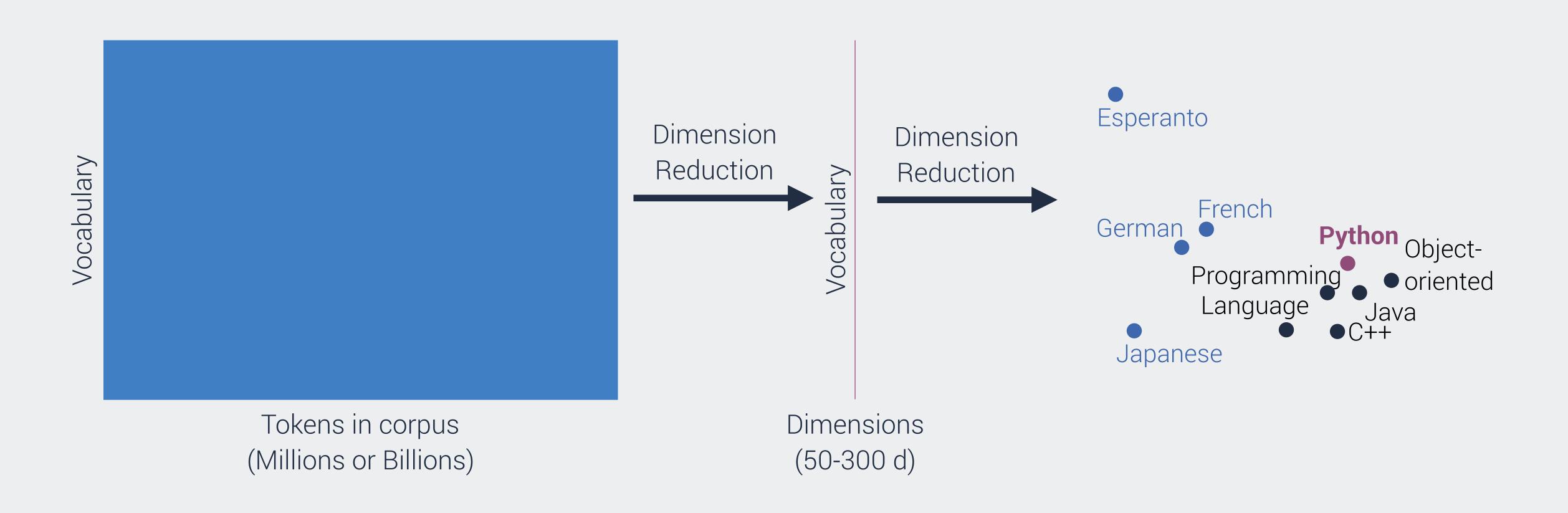
Word

Context



A simplified representation of word vectors

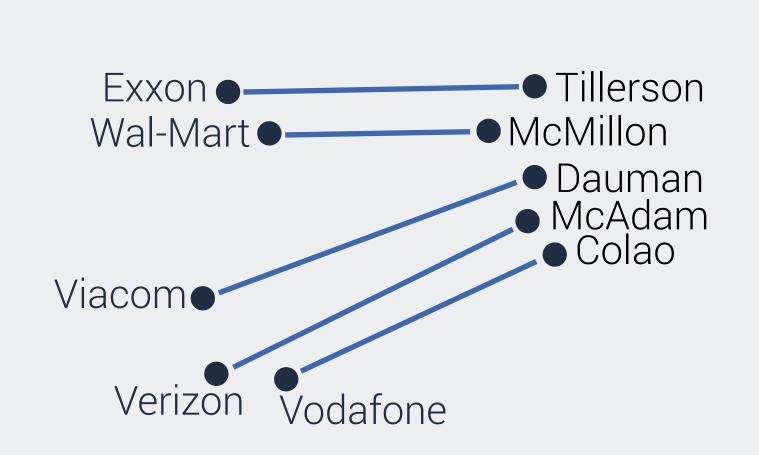
Dimension reduction is key to all types of embeddings models

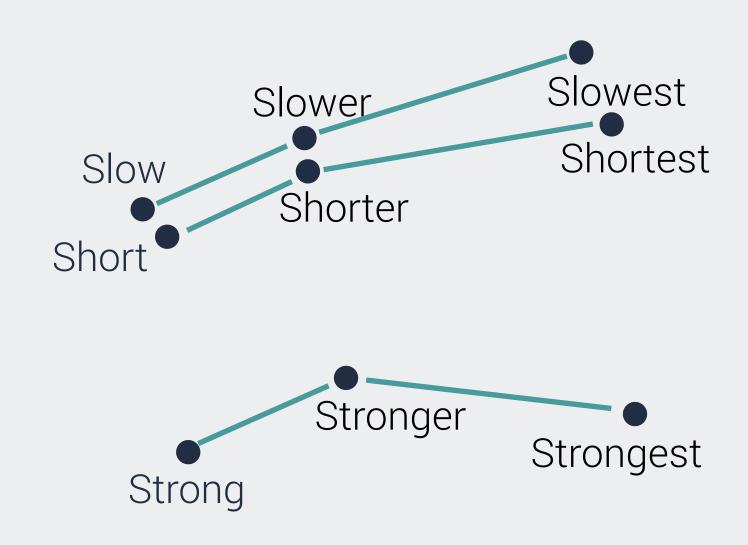


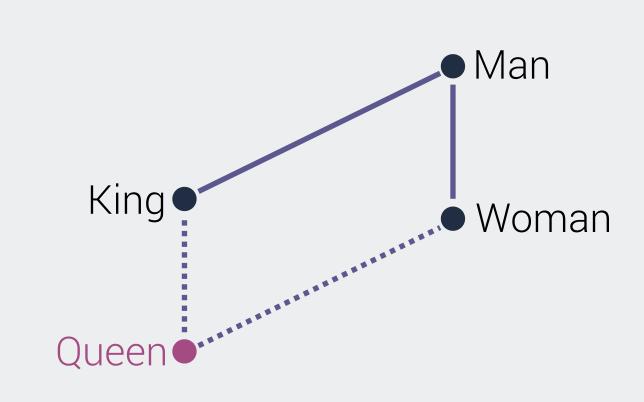


Embeddings capture entity relationships

Dimensionality enables comparison between word pairs along many axes







Hierarchies

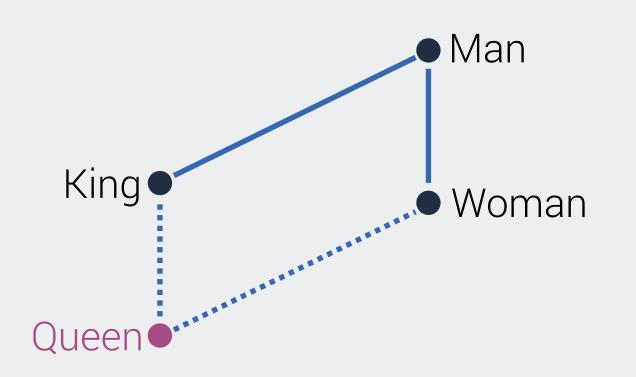
Comparatives and Superlatives

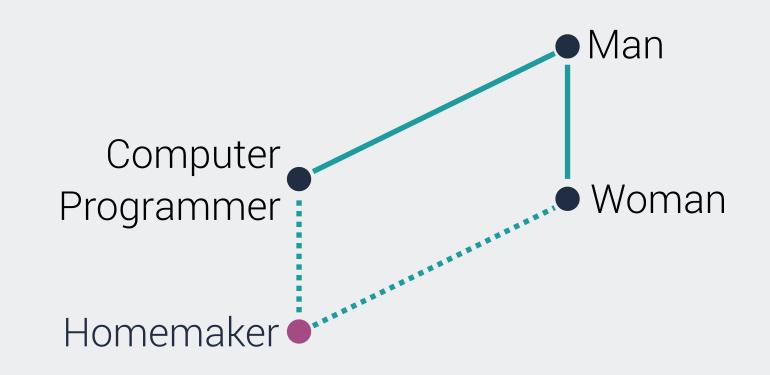
Man :: King as Woman :: ?



Embeddings reflect cultural bias in corpora

High dimensionality enables some bias reduction





Man :: King as Woman :: ?

Man :: Programmer as Woman :: ?



Pretrained embeddings facilitate fast prototyping

Embeddings training should match corpus that is being tested on

Corpus Generation	Corpus	Twitter	Common Crawl	GoogleNews	Wikipedia
	Tokens	27 B	42-840 B	100 B	6 B
Corpus Processing	Vocabulary Size	1.2 M	1.9-2.2 M	3 M	400 k
Language Model	Algorithm	GLoVE	GLoVE	word2vec	GLoVE
Generation	Vector Length	25 - 200 d	300 d	300 d	50 - 300 d
Language Model Tuning Final Application					



Problems with pretrained embedding models

Casing	Abbreviations vs Words e.g. IT vs it
Out of Vocabulary Words	Domain Specific Words & Acronyms
Polysemy	Words with multiple meanings e.g. drive (a car) vs drive (results) e.g. Chef (the job) vs Chef (the language)
Multi-word Expressions	Phrases that have new meanings e.g. Front-end vs front + end

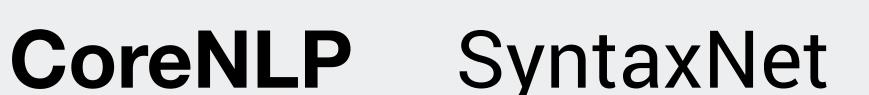


Custom language models tools

Modularized for different data and modeling requirements









Tokenization, POS tagging, Sentence Segmentation, Dependency Parsing









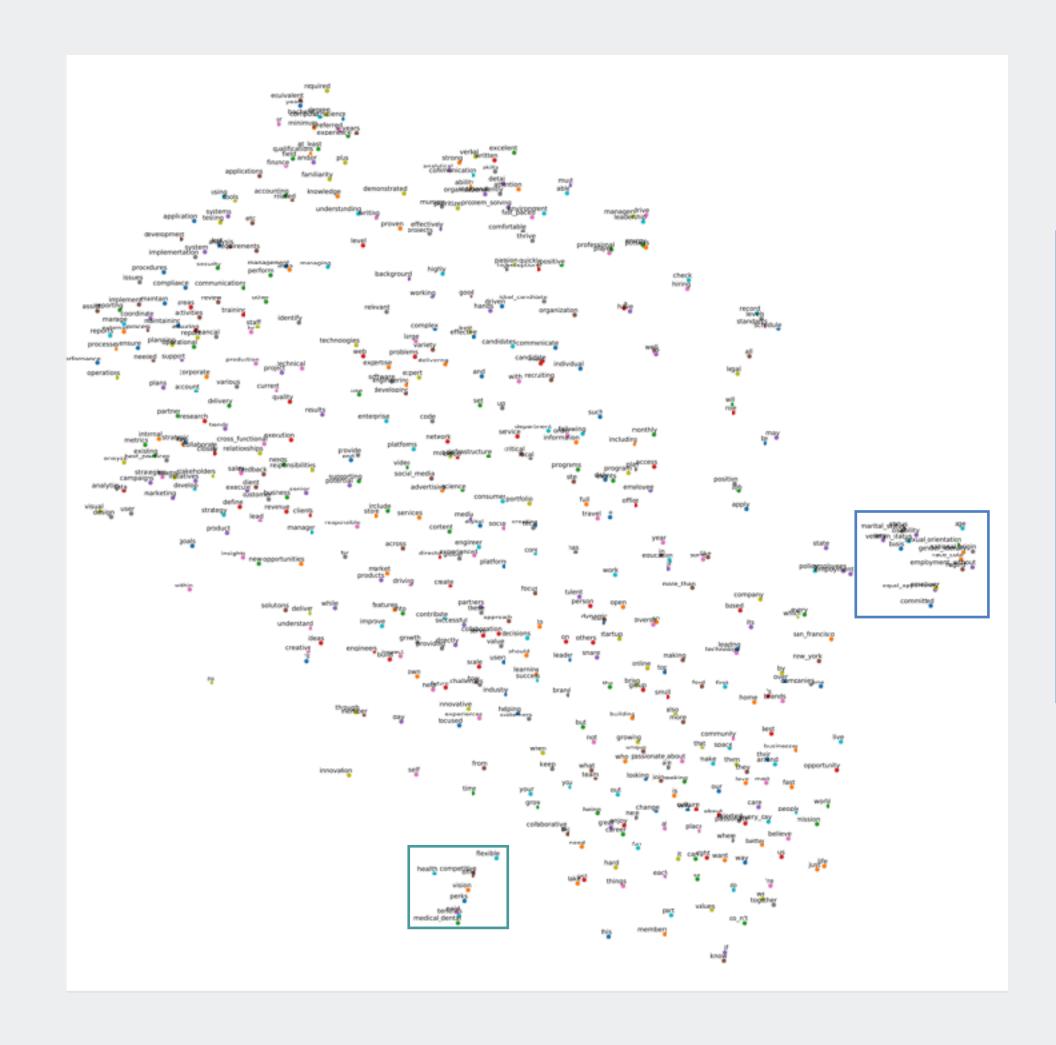
Language Modeling

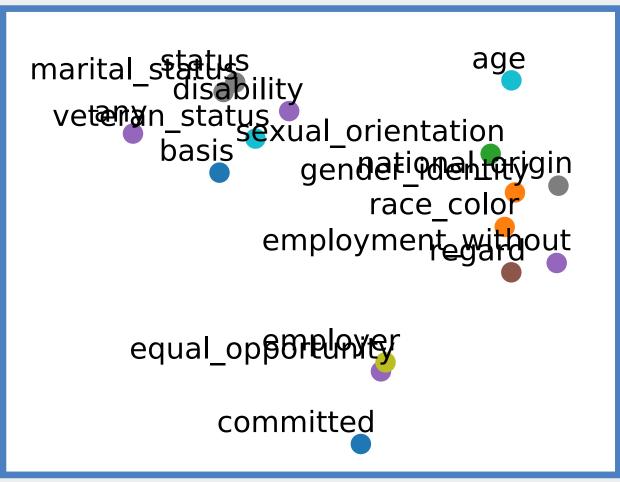
Different word embedding models (GLoVE, word2vec, fastText)

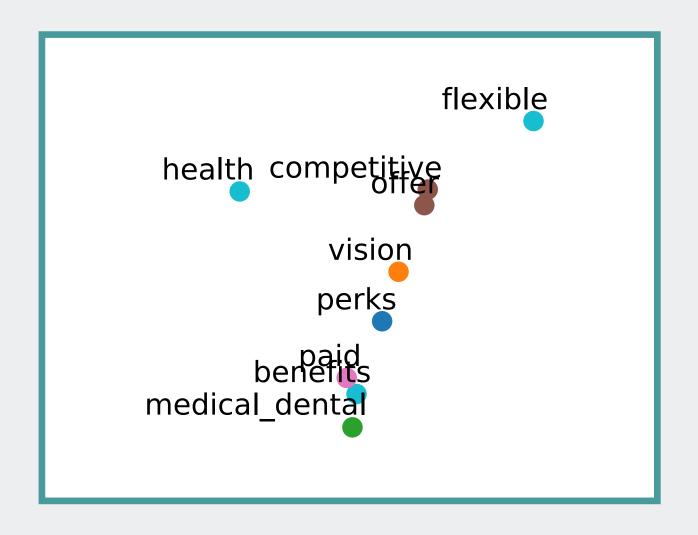


Career language embedding model

Identified equal opportunity and perks language



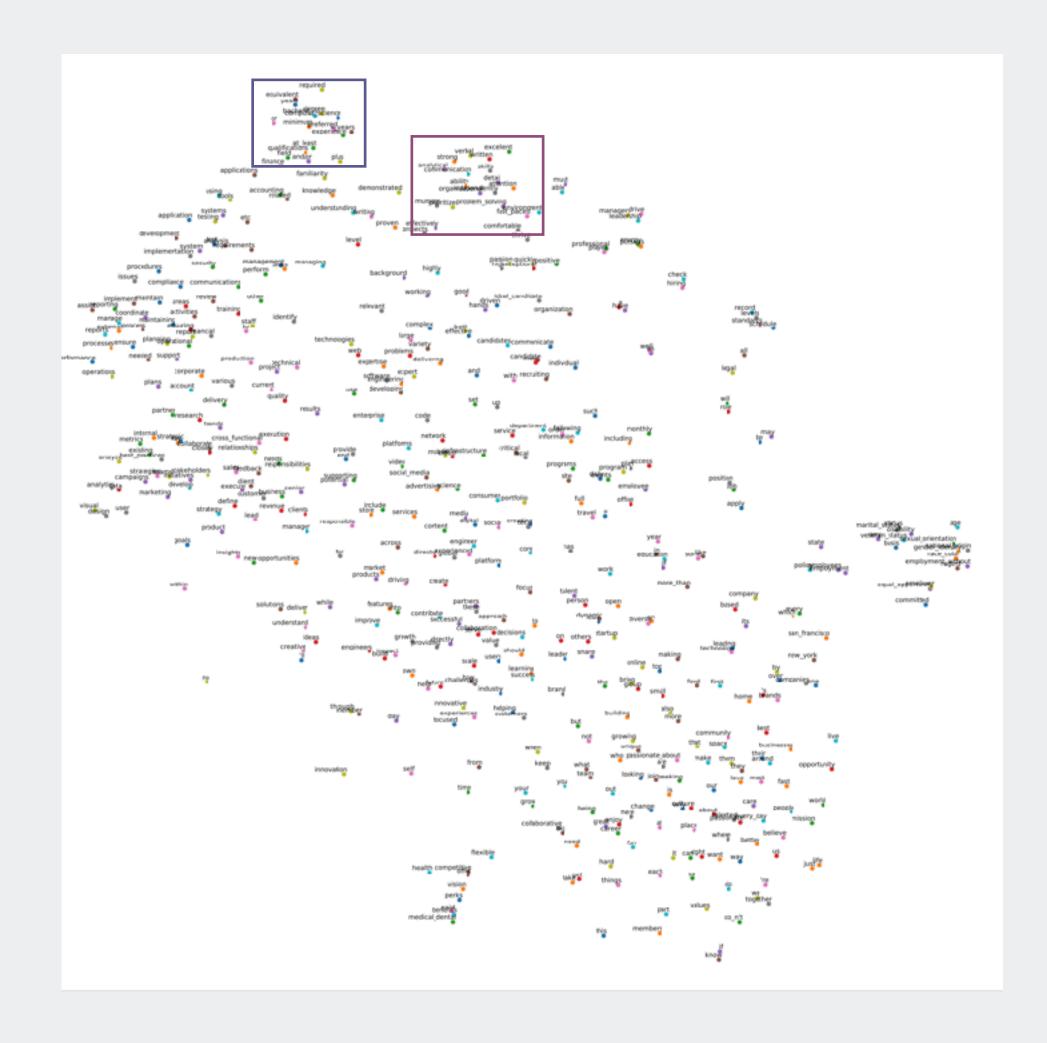




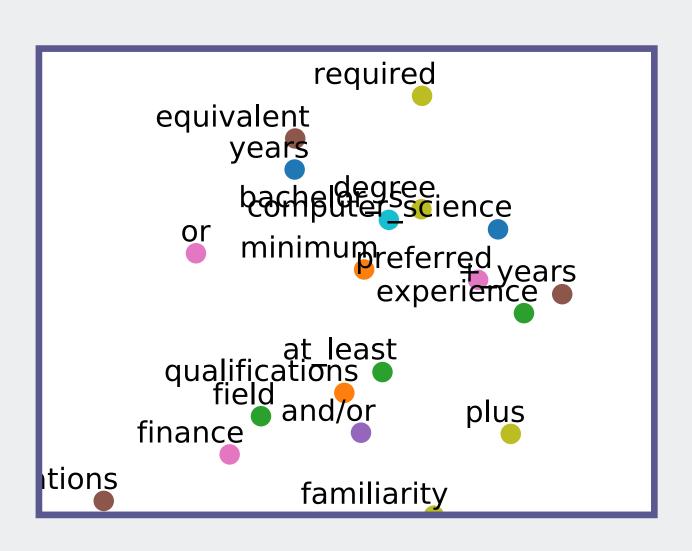


Career language embedding model

Identified 'soft' skills and language around experience



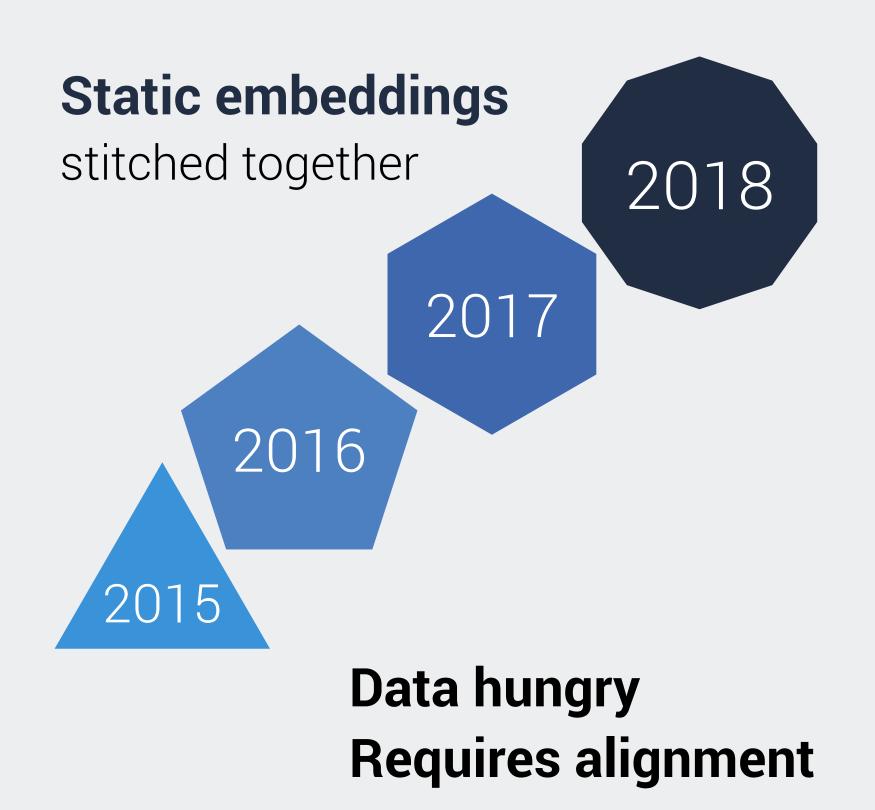




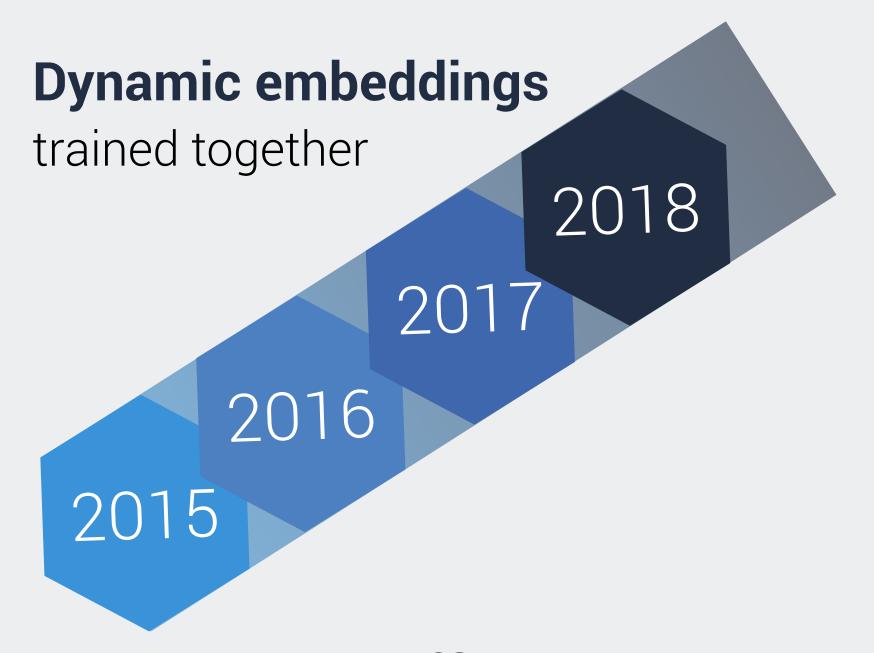


I've got 300 dimensions... but time ain't one

Two approaches to connect embeddings



Kim, Chiu, Kaneki, Hedge and Petrov, <u>arXiv: 1405:3515</u>. Kulkarni, Al-Rfou, Perozzi and Skiena, <u>arXiv: 1411:3315</u>.



Data efficient
Does not require alignment

Balmer and Mandt, <u>arXiv: 1702:08359</u> Yao, Sun, Ding, Rao and Xiong, <u>arXiv: 1703:00607</u>

Rudolph and Blei, arXiv: 1703:08052



Dynamic Bernoulli embeddings

Outputs facilitate quick analysis of trends

Absolute drift

Identifies top words whose usage changes over time course

words with largest drift (Senate)			
IRAQ	3.09	coin	2.39
tax cuts	2.84	social security	2.38
health care	2.62	FINE	2.38
energy	2.55	signal	2.38
medicare	2.55	program	2.36
DISCIPLINE	2.44	moves	2.35
text	2.41	credit	2.34
VALUES	2.40	UNEMPLOYMENT	2.34

Embedding neighborhoods

Extract semantic changes by nearest neighbors of drifting words

	UNEMPLOYMENT	
1858	1940	2000
unemployment	unemployment	unemployment
unemployed	unemployed	jobless
depression	depression	rate
acute	alleviating	depression
deplorable	destitution	forecasts
alleviating	acute	crate
destitution	reemployment	upward
urban	deplorable	lag
employment	employment	economists
distressing	distress	predict



Experiments with dynamic embeddings

	Small Corpus
Job Types	All
Time Slices	3 (2016-2018)
Number of Documents	50 k
Vocabulary Size	10 k
Data Preprocessing	Basic
Embedding Dimensions	100 d



Small corpus identified MBAs and PhDs

Reduced requirement for advanced degrees in many jobs

Demand for MBAs is Falling

MBAs in All Jobs

MBAs in DS Jobs

MBAs in Tech Jobs

-35% -15% +30%

Demand for PhDs is Falling

PhDs in All Jobs

PhDs in DS Jobs

PhDs in ML Jobs

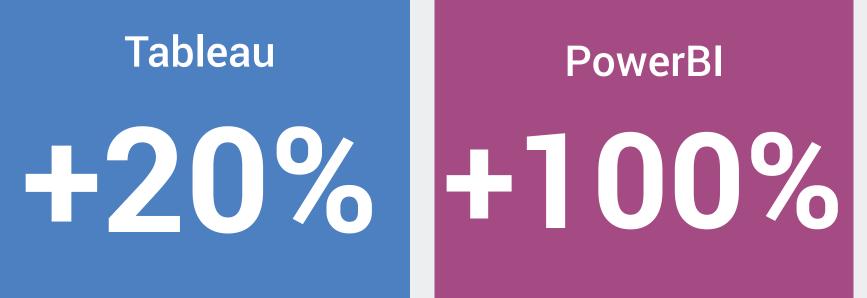


Small corpus identified skill demands

Data Viz is up and Hadoop (but not Spark) is down

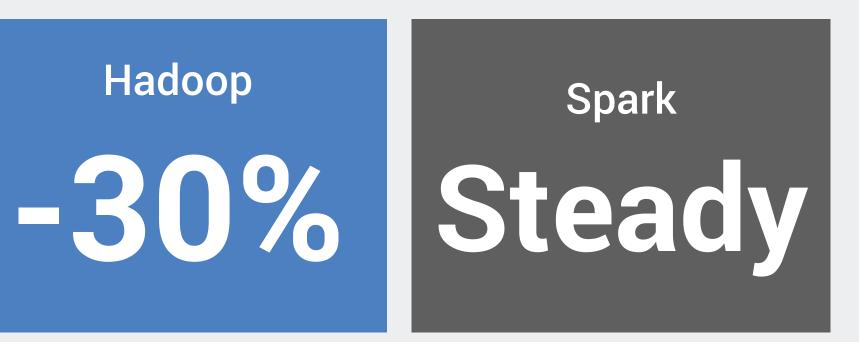
Demand for Data Visualization tools is up





Demand for Hadoop is down in DS and ML roles





Blue boxes indicate phrases identified from top drifting words analysis. Grey and pink boxes indicate 'control' skills. tap Recruit.co

Battle of the Languages

Difference between supply vs demand of scripting languages

Demand for Perl is down

Perl

Python -40% Steady



Python, the fastest-growing major programming language, has risen in the ranks of programming languages in our survey yet again, edging out Java this year and standing as the second most loved language (behind Rust).

Battle of the Languages

Difference between supply vs demand of scripting languages

Demand for Python up in Tech roles

Python in Tech Jobs

Python in DS Jobs +30% Steady

Demand for Java is up

Java in Tech Jobs

Java in DS Jobs



Python, the fastest-growing major programming language, has risen in the ranks of programming languages in our survey yet again, edging out Java this year and standing as the second most loved language (behind Rust).

Blue boxes indicate phrases identified from top drifting words analysis. Grey and pink boxes indicate 'control' skills. tap Recruit.co

Experiments with dynamic embeddings

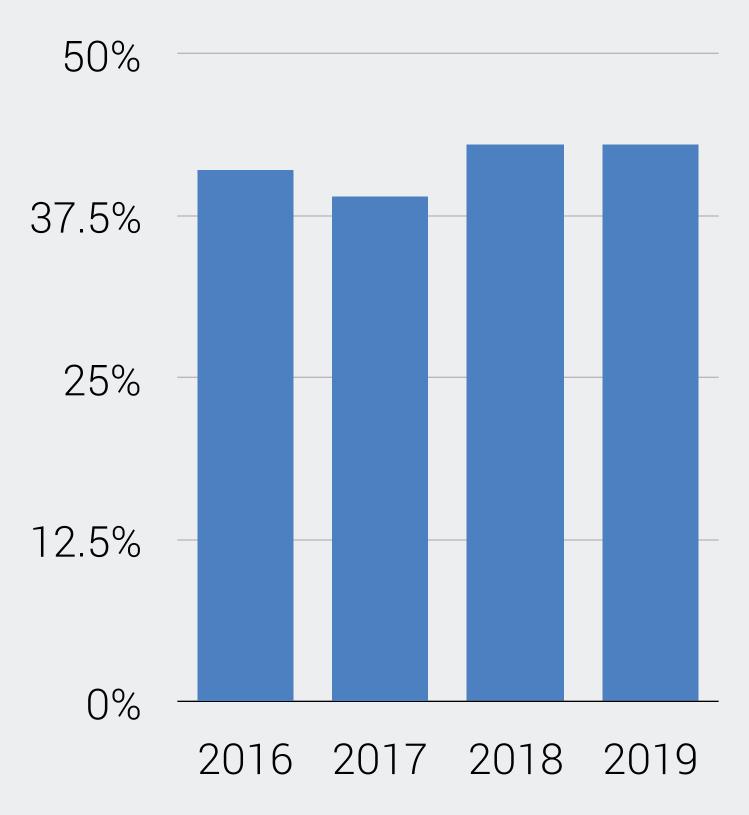
	Small Corpus	Large Corpus
Job Types	All	All
Time Slices	3 (2016-2018)	3 (2016-2018)
Number of Documents	50 k	500 k
Vocabulary Size	10 k	10 k
Data Preprocessing	Basic	Basic
Embedding Dimensions	100 d	100 d



SQL was a top drifting word

Large corpus identified role-type dependent shifts in requirements

Data Science & Tech Jobs



SQL requirement increases in specific functions





Beyond word2vec

- Flavors of static word embeddings: The Corpus Issue
- Considerations for developing custom embedding models
- Dynamic Bernoulli embeddings are robust with small datasets

How have tech and data science skills changed?

- Demand for MBAs and PhDs is falling
- Core Skills: DataViz & Scripting Languages
- Commodification of distributed systems impacts demand for Hadoop
- Demand for SQL in a variety of core business functions

Thank you Al Conference!

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