Applying Dynamic Embeddings in Natural Language Processing to Analyze Text

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Skills and qualifications matter in job descriptions

Same title, Different job

Finance Manager Kraft Foods

Junior (3 Years)

No Managerial Experience

Finance Manager
Roche

Senior (6-8 Years)

Division Level Controller

Strategic Finance Role

MBA / CPA

Same Title

Required Experience

Required Responsibility

Preferred Skill

Required Education

Different title, Same job

Performance Marketing Manager PocketGems

Mid-Level

Quantitative Focus

iBanking Expertise

Data Analysis Tools (SQL)

Consulting Experience Preferred

MBA Preferred

Senior Analyst, Customer Strategy

The Gap

Mid-Level

Quantitative Focus

Finance Expertise

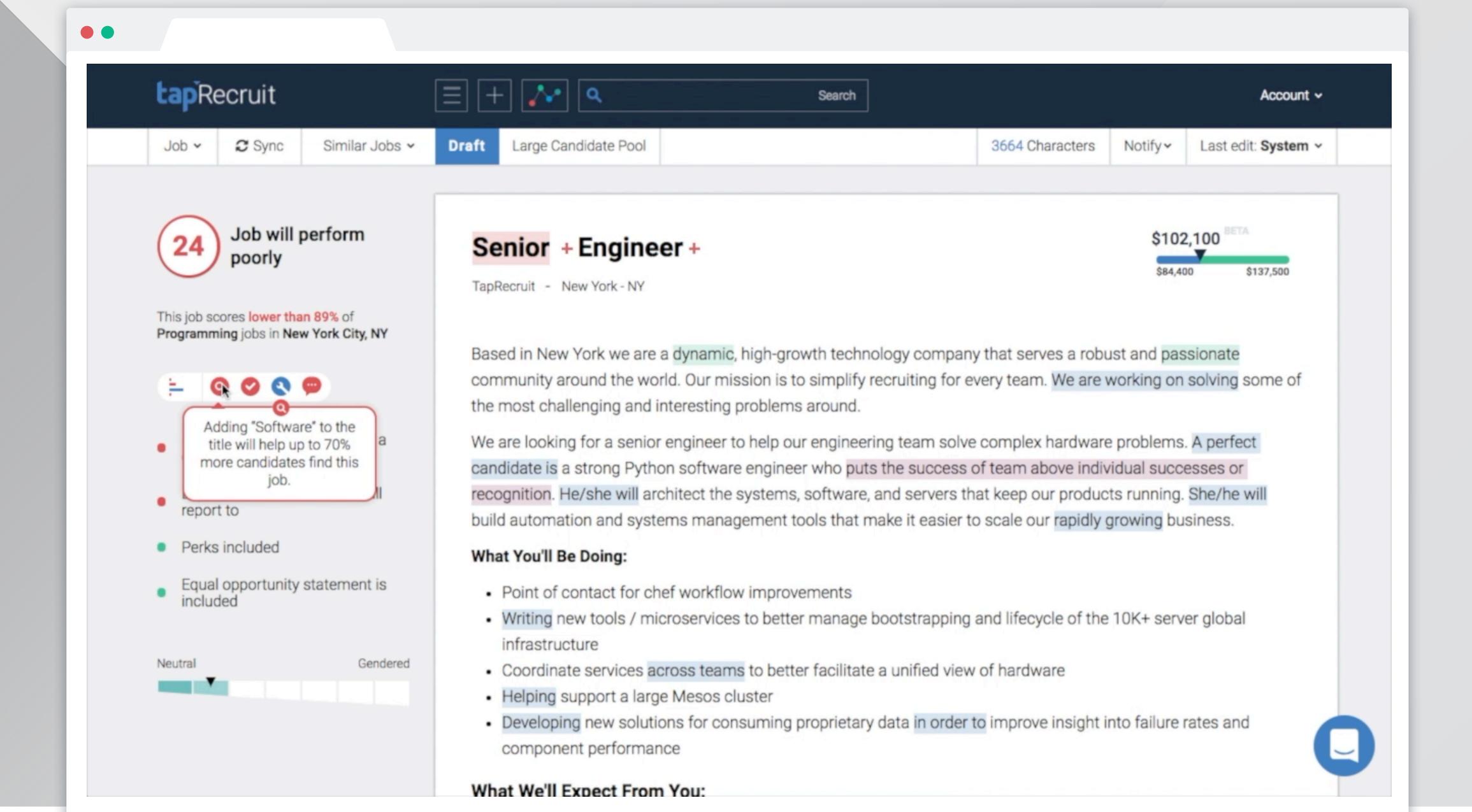
Relational Database Experience

External Consulting Experience Preferred

BA in Accounting, Finance, MBA Preferred

- Required Experience
- Required Skills
- Required Experience
- Required Skills
- Preferred Experience
- Preferred Education





Research at TapRecruit

What are distinguishing characteristics of successful career documents?

NLP and Data Science:

- What are distinguishing characteristics of successful career documents?
- What skills are increasingly important for different industries?
 Calibrating labor supply and demand

Decision Science:

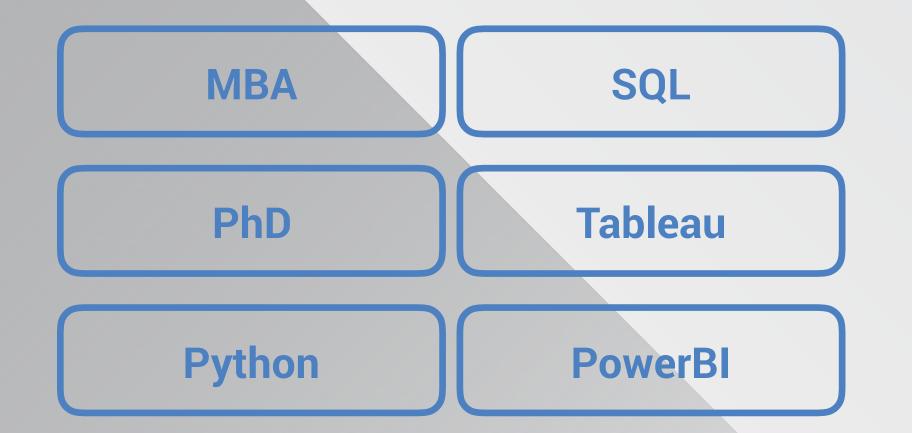
- How do candidates make decisions about which jobs to apply to?
- How do hiring teams make decisions about candidate qualifications?

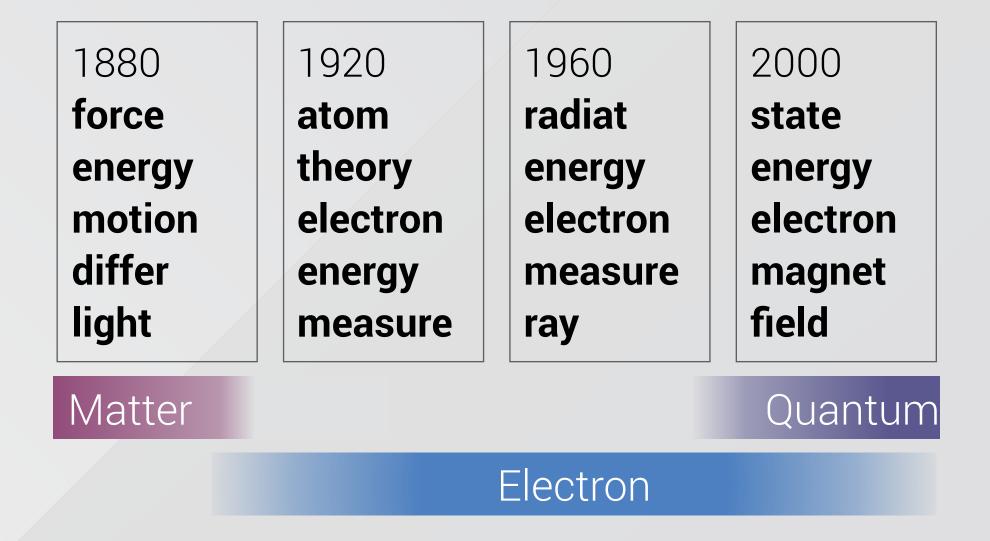


How have data science skills changed over the last few years?

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

Adapted from Blei and Lafferty, ICML 2006.



Word embeddings use context to extract meaning

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 Word Context

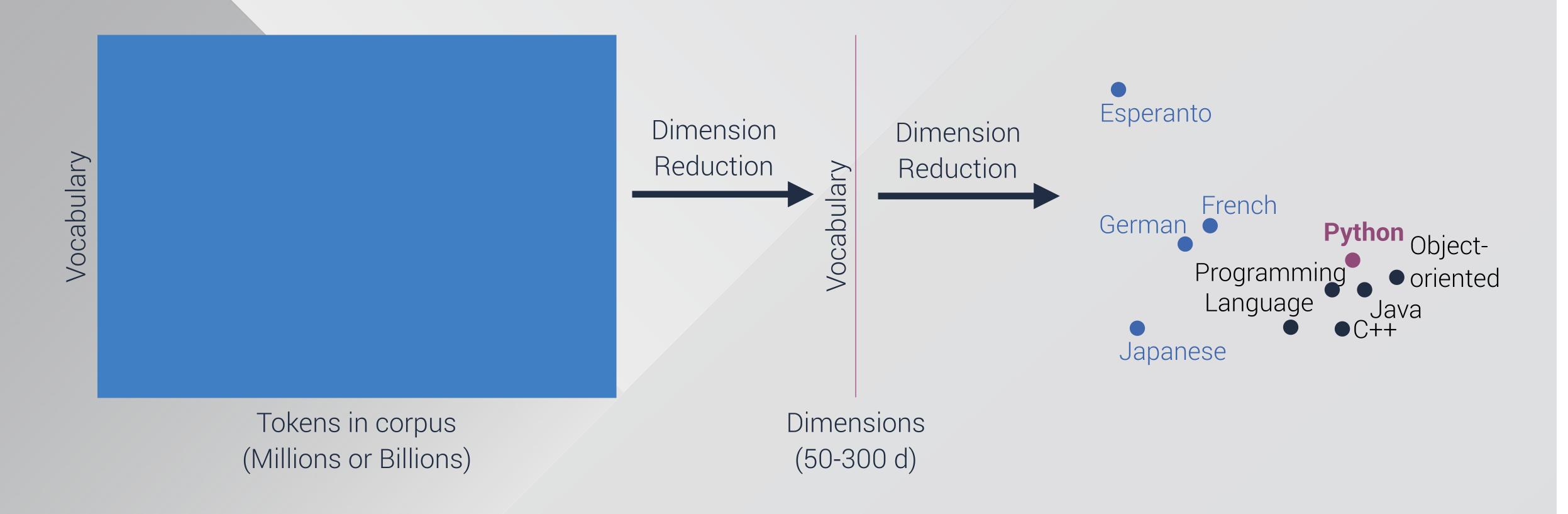
Proficiency programming in Python, Java or C++.

Context Word Context



A simplified representation of word embeddings

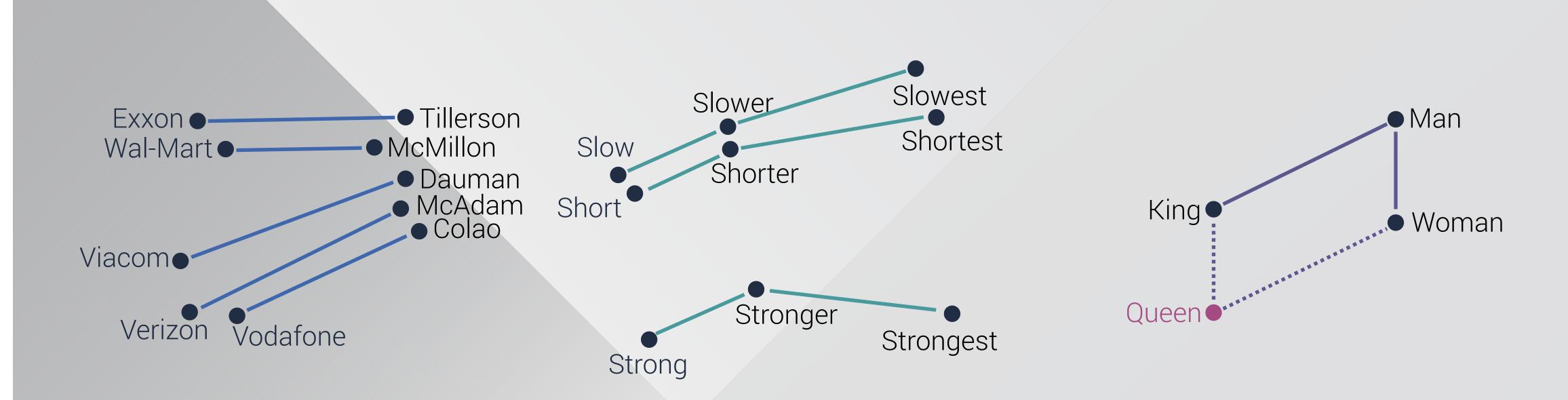
Dimension reduction is key to all types of embeddings models





Word embeddings capture entity relationships

Dimensionality enables comparison between word pairs along many axes



Hierarchies

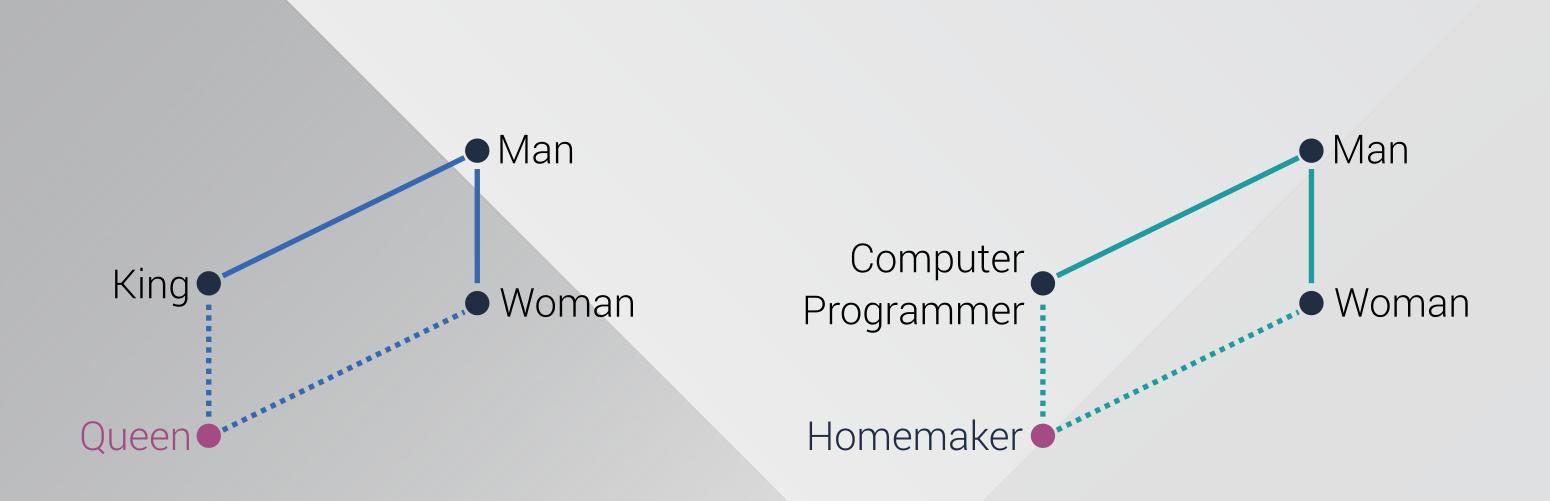
Comparatives and Superlatives

Man :: King as Woman :: ?



Word embeddings reflect cultural bias in corpora

High dimensionality enables some bias reduction



Man :: King as Woman :: ? Man :: Programmer as Woman :: ?



Pretrained word embeddings enable fast prototyping

Corpus Generation

Corpus Processing

Language Model Generation

Language Model Tuning

Final Application

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



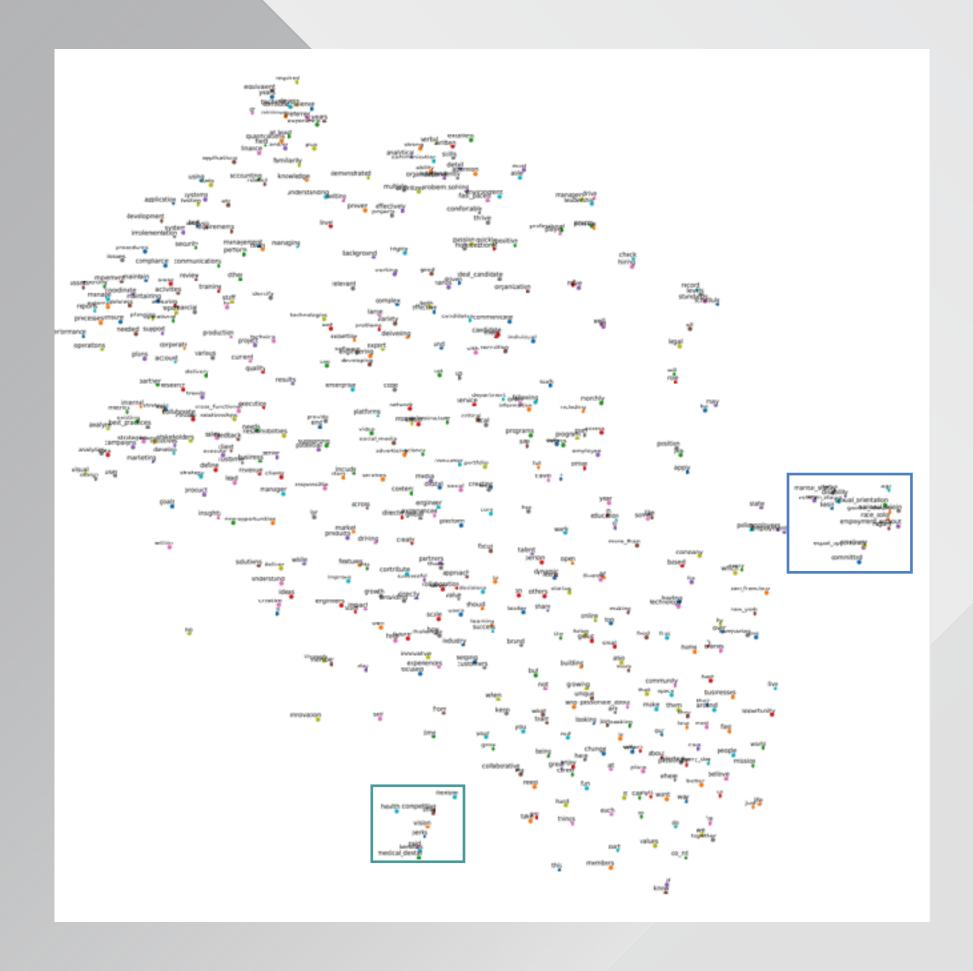
Drawbacks of pretrained word embeddings

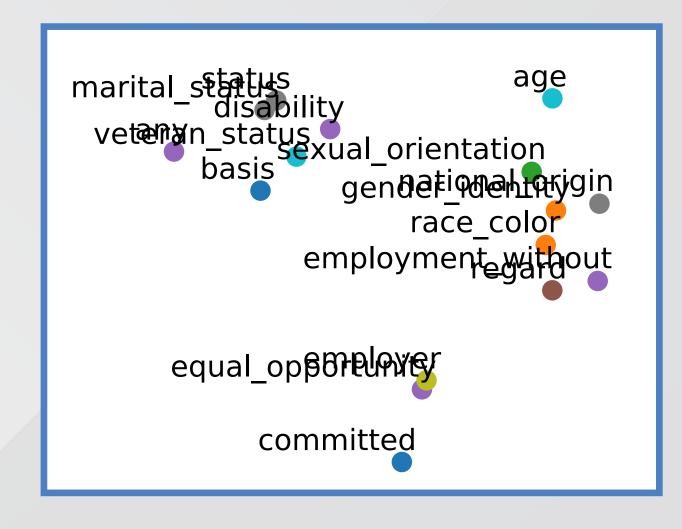
Casing	Abbreviations vs Words e.g. IT vs it	
Out of Vocabulary Words	Domain Specific Words & Acronyms	
Polysemy	Words with multiple meanings e.g. drive (a car) vs drive (results) e.g. Chef (the job) vs Chef (the language)	
Multi-word Expressions	Phrases that have new meanings e.g. Front-end vs front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

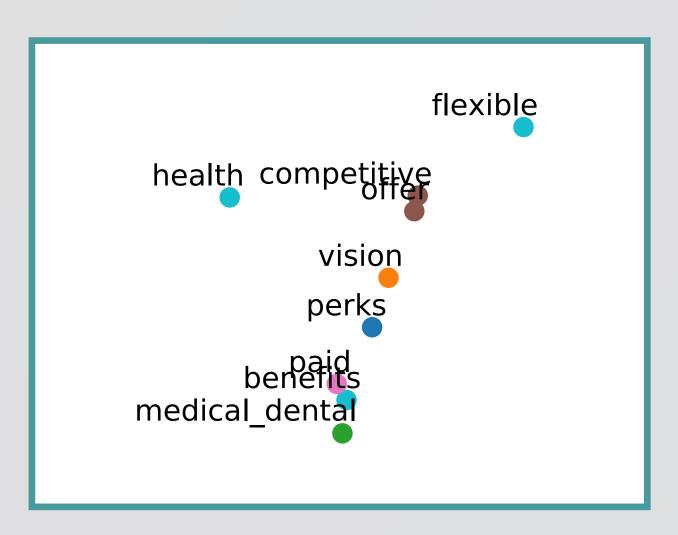


Career language embedding model

Identified equal opportunity and perks language







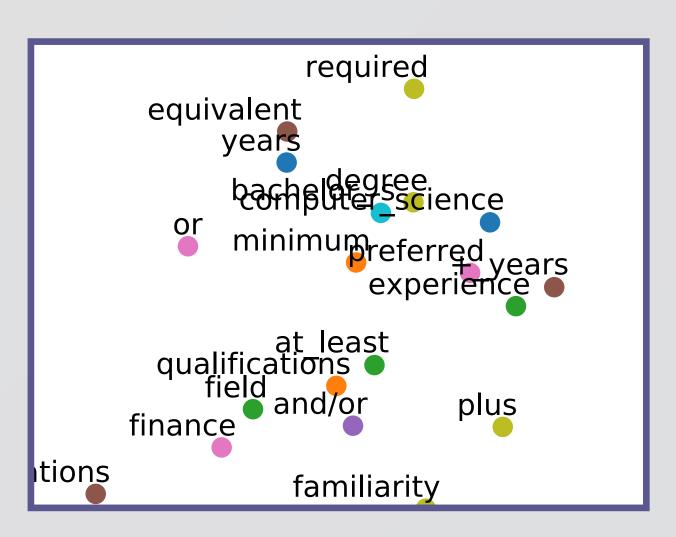


Career language embedding model

Identified 'soft' skills and language around experience



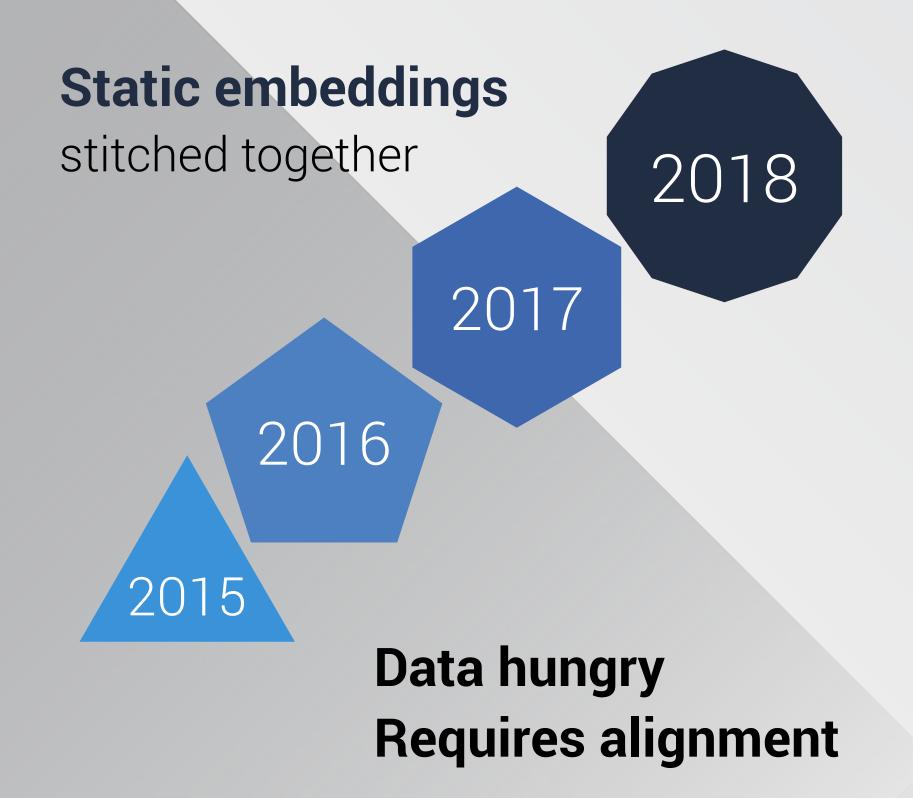


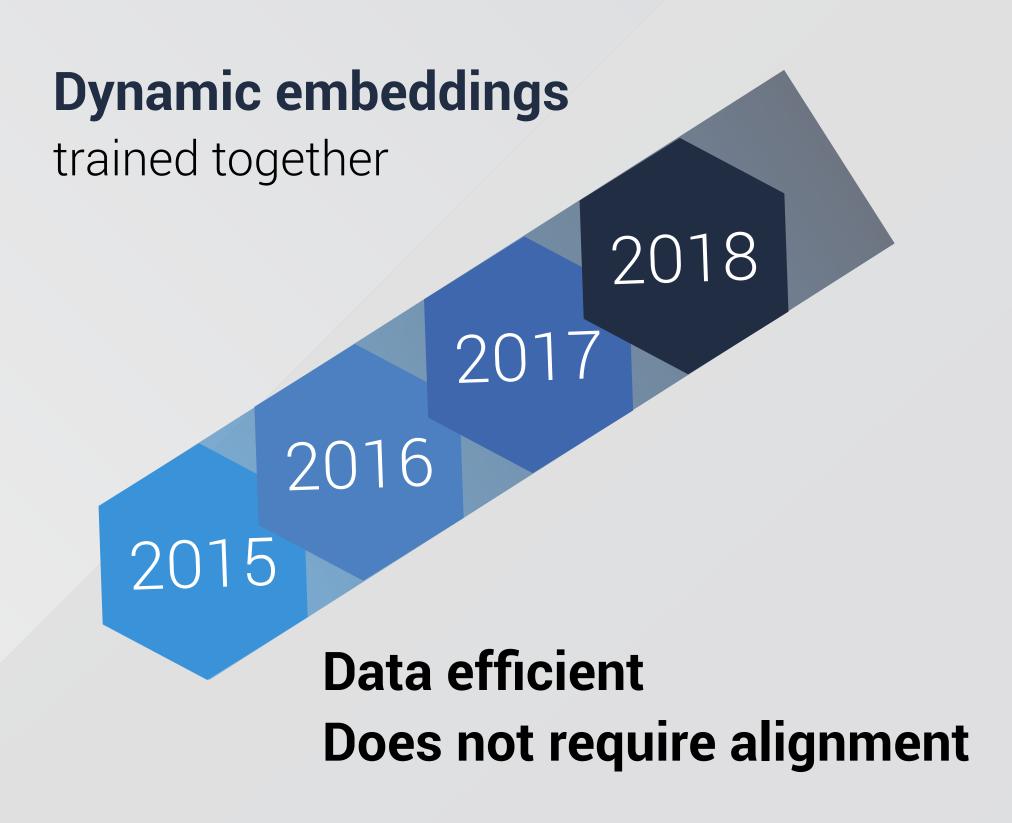




l've got 300 dimensions... but time ain't one

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>.

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	

Repository Link: http://bit.ly/dyn_bern_emb



Experiments with dynamic embeddings

	Small Corpus
Job Types	All US Jobs
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 in US Roles

MBAs in All Jobs

MBAs in DS Jobs

MBAs in Tech Jobs

-35% -15% +30% -40%

and in Roles based in the UK

MBAs in All Jobs

MBAs in Tech Jobs

Demand for PhDs is Falling in US Roles

PhDs in All Jobs

PhDs in DS Jobs

PhDs in ML Jobs

and in Roles based in the UK

PhDs in DS Jobs

PhDs in ML Jobs



Small corpus identified skill demands

Data Viz is up in lots of different roles

Demand for Data Visualization tools is up

Tableau

PowerBI

+20% +100%

Data Viz growth in US Non-DS Roles

Data Viz in DS Jobs

Data Viz in Other Jobs

+30% +90%

and UK Non-DS Roles

Data Viz in DS Jobs

Data Viz in Other Jobs

+30% | +200%



Small corpus identified skill demands

Demand for Hadoop (but not Spark) is down in Data Science jobs

Data Science Jobs

Hadoop

Spark

-30% Steady +100%

AWS

Tech Jobs (non-DS)

Hadoop

Steady

Spark

AWS



Battle of the languages: Supply vs Demand

Demand for Perl is down in Data Science Roles

Perl

Python -40% Steady

Java -60%



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: Supply vs Demand

Scripting Languages absorbing changes

Data Science Jobs

Java

-60% Steady

Python

Scripting Languages

+140%

Tech Jobs (non-DS)

Java

Steady

Python

Scripting Languages



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).



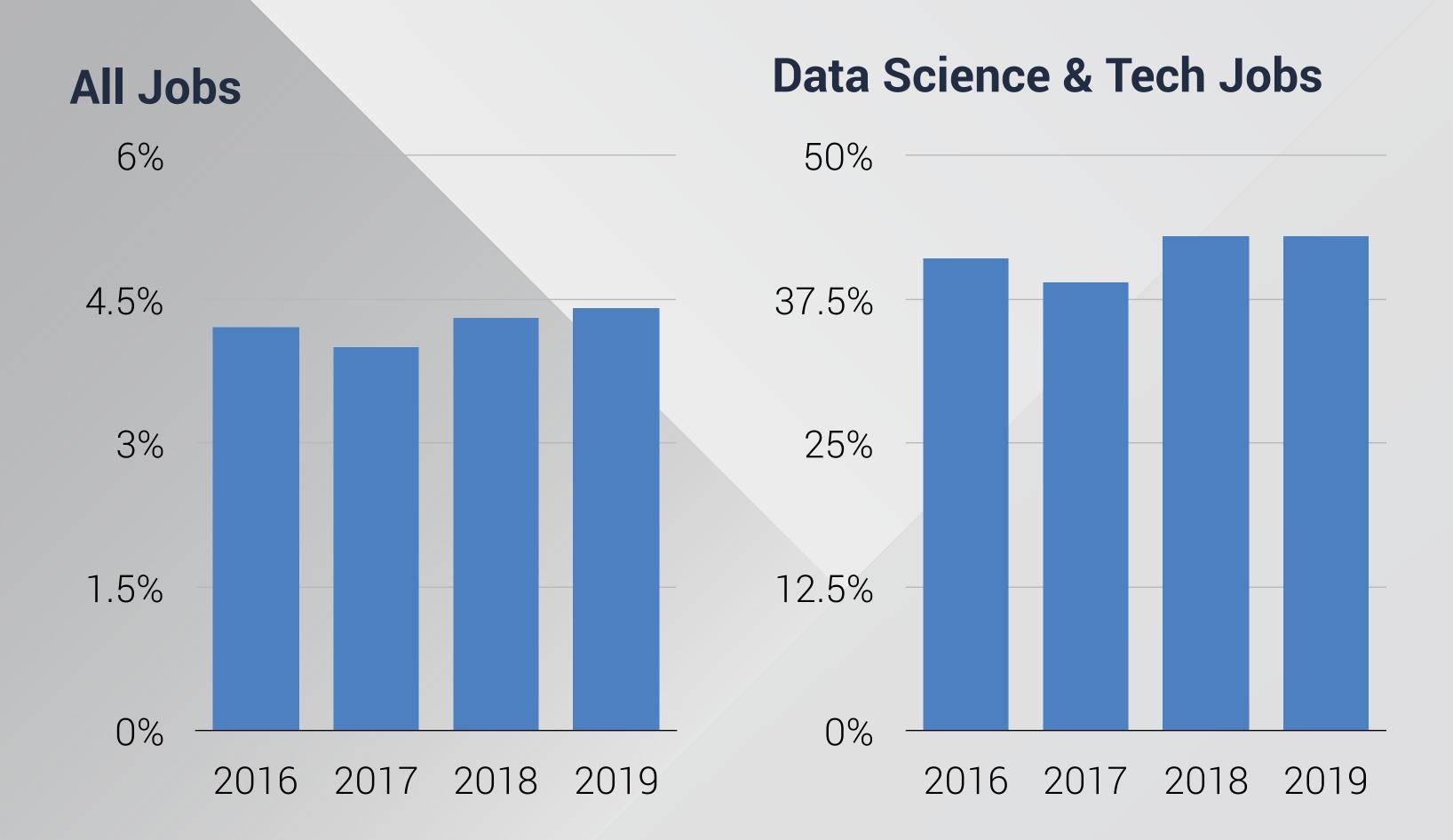
Experiments with dynamic embeddings

	Small Corpus	Large Corpus
Job Types	All US Jobs	All US Jobs
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



Large corpus identified SQL as a top drifting word

But no difference in demand for SQL in jobs





Large corpus identified SQL as a top drifting word

Large corpus identified role-type dependent shifts in requirements

SQL requirement increases in specific functions





Beyond word2vec

- Flavors of static word embeddings: The Corpus Issue
- Considerations for developing custom embedding models
- Dynamic 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 Rev2!

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